GEOGRAPHIC COMPETITION IN EMERGENCY DEPARTMENT SERVICES

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Abstract

The utilization of emergency services in the United States has increased substantially in the last 20 years. Despite this trend, the number of emergency departments (EDs) has not increased on par with the volume of patients that seek emergency services. Hospitals are expanding the provision of emergency services through freestanding emergency departments (FSEDs), independent facilities managed by hospitals (but not physically attached to them) that can provide the same services as traditional EDs. It is not clear how the entry or exit of EDs affect emergency care utilization. I analyze the effect of ED entry and exit on ED utilization and emergency-related health care outcomes. In addition, I analyze how FSEDs affect the risk profile of the inpatient population at hospitals with FSEDs nearby and at hospitals that operate FSEDs. I find an asymmetric effect on incumbent ED number of visits of entry and exit of EDs. Increases in the number of visits due to ED entry are not correlated with changes in emergency-related mortality rates. Hospitals that operate FSEDs have an inpatient population with higher acuity than hospitals that don't operate FSEDs, and hospitals with FSEDs nearby have an inpatient population with lower acuity than hospitals that don't.

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INTRODUCTION

Emergency departments (ED) are key providers of health services, particularly for the uninsured and low-income population (Billings et al., 2000a). EDs are not only effective settings to treat urgent care, but also are providers of ambulatory care (Institute of Medicine, 2007). The ED is a significant source of patients for hospitals (Morganti et al., 2013) and inpatient admissions originated in the ED have a higher margin than inpatient admissions originated elsewhere (Henneman et al., 2009). Estimates show a 7.8 percent profit margin for EDs in 2009. ED utilization increased substantially in the last 20 years, and is expected to increase as health insurance coverage increases (Skinner et al., 2014; Taubman et al., 2014); the introduction of the Affordable Care Act did not slow the pace of ED utilization, but reduced the proportion of ED utilization by uninsured individuals (Singer et al., 2019). Despite this trend, the number of EDs has not increased on par with the number of visits (R. Y. Hsia et al., 2011; Liu et al., 2014). A higher volume of patients to EDs can lead to crowding. Crowded EDs have lower quality of care, lower patient satisfaction, poorer patient outcomes, and higher rates of patients who leave without being seen (Derlet et al., 2000; Sanchez et al., 2006; Weiss et al., 2005). A pressing question for both providers and policymakers is how the US health care system will either accommodate an increasing demand for emergency services (from either population growth or aging, or shortages of primary care) while maintaining or improving the quality of emergency care, or will focus on reducing the demand for emergency services. If the latter is insufficient, careful regulation of the supply of emergency services could prove more effective.

Hospitals are the principal providers of emergency services. However, the supply of emergency services does not necessarily follow the supply of other hospital services. Hospitals have been expanding ED capacity at the original location to meet increasing demand and to open access to inpatient services (Melnick et al., 2004). Some hospitals have expanded ED capacity by constructing satellite freestanding emergency departments (FSEDs) (Berger, 2011). The number of satellite FSEDs in the United States has more than tripled in the last decades (Patidar et al., 2016). Such facilities are owned and operated by hospitals but physically detached from the hospital campus. These facilities are generally open 24 hours a day and 7 days a week and are fully capable of treating high acuity patients (ACEP, 2013). Satellite FSEDs provide timely care similar to hospital-based EDs (Baehr et al., 2020b) Autonomous FSEDs are, on the other hand, owned and operated independently by groups not affiliated with a hospital, and may or may not provide the same level of care than hospital-affiliated emergency departments. With satellite FSEDs, hospitals can compete in different geographical markets that are otherwise underserved or have potential for market entry. In addition to FSEDs, other developments such as urgent care centers and retail clinics provide substitute services for ED use, in particular for low-complexity and low-acuity patients (D. Alexander et al., 2017).

The hospital market has faced several changes in recent years: mergers and consolidations (Cuellar et al., 2003), entries and exits (MedPAC, 2012), and the elimination of state-level Certificates of Need for the construction of hospitals (Conover et al., 1998), among others. At the same time, hospitals have faced increased competition from other players in the health services field, that are not necessarily covered by the supply regulations on inpatient services. For instance, the entry of freestanding ambulatory surgery centers is associated with lower revenues and profits at incumbent hospitals (Carey et al., 2011), and the entrance of cardiac specialty hospitals reduced health expenditures without worsening clinical outcomes (Barro et al., 2006). There is still a potential for new developments in health care that compete for services traditionally offered by hospitals.

Previous studies have shown that changes in the supply of health care influence access to care and health outcomes. Changes in the supply of hospital services affect access to health care and health outcomes. Some studies show limited decreases in access to care after hospital closures (Buchmueller et al., 2006) while other show more substantial decreases in access to care (Bazzoli et al., 2012; Wishner et al., 2016). Increased distance to hospitals is associated with increased mortality rates from myocardial infarctions and unintentional injuries (Buchmueller et al., 2006). Hospitals that are less efficient or in more competitive markets are more likely to close (Abraham et al., 2007; Capps et al., 2010). Closure of rural hospitals is associated with increased mortality from time-sensitive health conditions (Carroll, 2019) and has negative welfare effects for patients in the order of millions of dollars per hospital closed (McNamara, 1999); however, costs in surviving hospitals decreased (Lindrooth et al., 2003) and social welfare may increase if relatively inefficient hospitals close (Capps et al., 2010). With respect to other changes in health care supply, closures of large obstetric units led to increases in neonatal and perinatal mortality in the short run, but no changes in the medium run (Kozhimannil et al., 2018; Lorch et al., 2013). In addition to these direct effects, hospital closures have spillover effects: hospital closures induce price increases through an improvement in bargaining position of the remaining hospitals (Wu, 2008), and lower costs per adjusted admission through increases in inpatient admissions in neighboring hospitals (Lindrooth et al., 2003).

Emergency department closures are associated with increases in ambulance diversion and worse health outcomes.(R. Y.-J. Hsia et al., 2011; Liu et al., 2014; Shen et al., 2012, 2016; Sun et al., 2006). Restrictions on the entry of EDs, such as Certificates of Need (CON) increased length of stay for ED patients (Paul et al., 2014). EDs have lost visits to emergency care and convenience clinics that provide services that substitute emergency care (D. Alexander et al., 2017). In addition, the expansion of telehealth has provided access to healthcare to patients who would otherwise seek care at EDs (Ashwood et al., 2017; Champagne-Langabeer et al., 2019; Heath et al., 2009) and access to emergency medicine specialists to rural hospitals (Natafgi et al., 2018). On the other hand, emergency services often are over-utilized: the use of emergency services for non-urgent conditions increases health care costs and contributes to ED crowding (Bamezai et al., 2005; Billings et al., 2000b; Derlet et al., 2000; Robert Wood Johnson Foundation, 2013).

With respect to the expansion of emergency services via FSEDs, previous research shows a particular trend. Hospitals tend to open FSEDs in highly affluent areas with a larger proportion of white inhabitants (A. J. Alexander et al., 2019; Dark et al., 2017; Patidar et al., 2016), in areas with a payer mix biased towards commercial enrollees (Baehr et al., 2020a; Schuur et al., 2017), and areas further away from public transit lines in urban areas (Carlson et al., 2019). The introduction of FSEDs increased emergency care prices (Ho et al., 2017), is associated with higher Medicare costs (Patidar et al., 2017b) and higher ED utilization in commercially insured patients (Ho et al., 2019), but did not diminish the number of visits in hospital-based EDs (Xu et al., 2020) nearby. A comparison of FSED and hospital-based ED patients shows that FSED patients are more likely to be women, white, employed, and privately insured (Burke et al., 2019; Pines et al., 2018); hospital-based EDs are more likely to be admitted for inpatient care and stay a longer time in the ED (Burke et al., 2019; Pines et al., 2018; Simon et al., 2018). Following this evidence, the 2017 Medicare Payment Advisory Commission recommended a cut in reimbursement rates to FSEDs that open within 6 miles from a hospital-based ED (Freeman et al., 2020; MedPAC, 2017). On the other hand, supporters of FSEDs argue that they have the potential to expand access to emergency care (Harish et al., 2016) and provide timelier care than hospital-based EDs (Baehr et al., 2020b). Even if FSED entry occurs in more affluent areas, it could respond to a need for a higher supply of emergency services: for instance, if EDs are operating at capacity, or if the distance traveled to the ED compromises timely care. This can be particularly relevant in rural areas: the entrance of an FSED was associated with reducing access times in a regional emergency medical system (Lawner et al., 2016). There is anecdotal evidence that the convenience and low utilization of FSEDs offers additional benefits over hospital-based EDs for managing pharmacological crises (Tucci, Moiz Ahmed, et al., 2017) or psychiatric health emergencies (Tucci, Ahmed, et al., 2017).

This dissertation studies the effects of geographical competition of emergency services in health and economic outcomes. In particular, I study entry and exit of EDs and FSED and how they are related to changes in emergency services and inpatient utilization, and changes in health outcomes. As response time is critical in emergent conditions, easy access to emergency services is key for appropriate provision of emergency care. At the same time, if EDs are used inappropriately to provide care that is better provided elsewhere, easy access to emergency services could lead to inefficiencies and suboptimal use of healthcare resources. It is not my intent to discuss the appropriateness of a specific emergency service utilization, but to shed light on how geographic competition in emergency services could lead to emergency services utilization that doesn't correspond to improved health outcomes.

In Chapter 1 I analyze the changes in ED utilization after entry and exit of emergency departments in the geographic area of incumbent EDs. Following the transportation literature, where increases in installed capacity induce utilization (Goodwin et al., 2003; Noland, 2000; Weis et al., 2009), I test whether the local availability of emergency services increases utilization, or if the lack thereof decreases utilization. In particular, I analyze if the entrance or exit of EDs within a certain distance from incumbent EDs decreases or increases the number of visits of the incumbent ED. In this Chapter I introduce the National Emergency Departments Inventory (NEDI-USA), the main data source for this dissertation.

In Chapter 2 I assess whether the change in the local availability of emergency services is associated with health outcomes. With the results from Chapter 1 I calculate the total change in the number of visits diverted to or from the ED entrance of exit net of the expected number of visits of the incumbent ED. This measure shows the aggregate change in visits of ED entrance or exit. With these aggregated results I estimate the association between aggregated change in visits and mortality rates of emergency-related conditions. This is an indirect test of induced demand in emergency services. If the availability of emergency services induces demand, then, all else equal, changes in the supply of emergency care change access to ED services but have little effect in health outcomes. This definition of induced demand differs from the supplier-induced demand derived from either asymmetric information between providers and patients or from a behavioral change from providers facing a reduction in revenue: in this case, the source of the induced demand relies on the availability and convenience of ED services.

Lastly, Chapter 3 focuses on FSEDs and the effects of FSED location. Much has been studied about FSED location (in more affluent areas, as described before) and how they affect the provision emergency services (raise prices and costs and don't alleviate congestion, as described before), but it is yet not understood how they affect the provision of inpatient services. As EDs are a source of patients to the hospital (Morganti et al., 2013), FSEDs could serve as a mechanism to compete for inpatient services in a different geographical area than the parent hospital. Given what the research shows about FSED placement, it is possible that FSEDs are used as a tool for selecting good (i.e. low acuity or commercially insured) patients. I use information from Medicare Acute Inpatient Prospective Payment System to assess how the presence of FSED is associated with case and payer mix in hospitals nearby, and how operating an FSED is associated with case and payer mix in the parent hospital.

There are several policy implications of these questions. As some hospitals close and others expand via FSEDs, it has become paramount that policymakers understand the direct and indirect implications of the changes in the availability of emergency services while facing a constant increase in the demand for emergency services. Evidence of induced demand of emergency services due to the location of new EDs or evidence of cream skimming from FSEDs could influence policies on regulations for the entry of new EDs. Or if ED closures affect negatively health outcome and FSEDs do alleviate access to emergency or inpatient services, policies that help guide FSED locations to underserved areas would be in order.

CHAPTER 1. ENTRY AND EXIT OF EMERGENCY DEPARTMENTS AND EMERGENCY SERVICES UTILIZATION

Framework and Analytical Approach

Following the literature on hospital competition (Dranove et al., 2000; Gowrisankaran et al., 2003; Town et al., 2001), I model the emergency care market as monopolistic competition with differentiated products. Given the nature of emergency services, where timely access to care is critical to good health outcomes, the source of differentiation among EDs is geographical location. The literature extensively supports the importance of distance in emergency services: longer distances to EDs are associated with increases in mortality rates and decreases in utilization (Buchmueller et al., 2006; Lee et al., 2007; Liu et al., 2014). Other studies have found that the distance to the provider is among the relevant characteristics affecting the choice of an inpatient provider (Tay, 2003).

I borrow from the transportation literature to test for induced demand in the emergency services market. In this literature, the Braess paradox (Murchland, 1970) describes how increasing lanes on a highway does not reduce traffic congestion, but reducing lanes does. This phenomenon is well studied in transportation (Noland, 2000; Rapoport et al., 2009); as more driving lanes become available in a road, the incentives to use such road increase. These incentives divert drivers from alternative routes and alternative modes of transportation. Conversely, when a highway lane is closed, incentives to use the highway decrease, and some drivers take alternative routes or find alternative modes of transportation.

In this context, a recently opened ED will attract patients from incumbent EDs and will create incentives for patients –who otherwise are not using emergency services- to use emergency services. Conversely, a closed ED will divert some patients to other open incumbent EDs and will stop other patients –who otherwise would have used emergency services at the closed ED- to not use emergency services. By itself, the existence of an increase or decrease in visits due to the entry or exit of EDs doesn't indicate induced demand. For instance, in a previously underserved area (where EDs are few and far between, or where the installed capacity of EDs is low), the increase in visits after opening an ED could be evidence of pent-up demand. In a similar fashion, a decrease in visits after an ED closure could be evidence of lack of access for patients with truly emergent conditions. Everything else equal, these previous cases would affect emergency-related health outcomes. If a new ED facilitates access to emergency care in an otherwise underserved area, one would expect a reduction in mortality rates of conditions that could be treated successfully at an ED. In the case of an ED exit, one would expect an increase in mortality rates. I test for induced demand by estimating the correlation between the changes in predicted visits due to entry and exit of EDs and changes in mortality rates of emergency-related conditions; under the hypothesis of induced demand, this correlation is zero.

Following a circular Salop model (Salop, 1979), I model the emergency services market as EDs competing for patients in a market where prices are homogeneous and the source of product differentiation comes from the firms' geographical location. A violation of the price homogeneity assumption implies that product differentiation among EDs is not only geographic, and that prices influence emergency care utilization. Estimates of the price elasticity of emergency care utilization are low (-0.04 in Ellis et al., 2017), which gives credence to the price homogeneity assumption.

Heterogeneous consumers are located in a circle of radius m, following a distribution of consumer characteristics Z with CDF $F(Z;\Theta)$ and PDF $f(Z;\Theta)$ where parameter Θ denotes consumer preferences. N_m number of EDs are located along this circle and compete for patients based on their location. For simplification, I assume firms follow the maximal differentiation principle (Hotelling, 1929) and they locate equidistant from each other, at a normalized average distance $2\pi m/N_m$. Consumers have unit demands and derive utility u from using emergency services. However, consumers have a threshold $\bar{u}(\bar{d},h)$ at which they decide to use emergency services. This threshold depends positively on $\bar{d}$, the distance to the closest ED, and negatively on $h \in Z$, a privately-observed level of health status complexity. All else equal, a longer distance to an ED increases the threshold and reduces the likelihood of a consumer using emergency services. More complex health status decreases the threshold and increases the likelihood of a consumer using emergency services.

A consumer located at distance d between EDs i and j is indifferent between both EDs if this condition holds:

$$u - p_i - d = u - p_j - (2\pi m/N_m - d) \geq \bar{u}(\bar{d},h) \tag{1}$$

where $2\pi m$ is the length of the circumference of the circle with radius m. An interior solution occurs for consumers whose health status and distance to the closest ED yield a threshold low enough for them to use emergency care. I denote the set of consumers for which this happens as Υ. The interior solution for d is

$$d = \frac{p_j - p_i + 2\pi m/N_m}{2} \tag{2}$$

Since product differentiation comes from geographic location, other characteristics such as prices are determined homogenous, so $p_i = p_j$. As ED i serves patients on both sides of the circle, the volume V_i of patients ED i serves is given by

$$V_i = \int_{Z\in\Upsilon} 2d_i f(X;\Theta)dX = \int_{Z\in\Upsilon} \frac{2\pi m}{N_m} f(X;\Theta)dX \tag{3}$$

$$V_i = Q(Z, N; \Theta, m) \tag{4}$$

where $Q(\cdot)$ is a general function that relates consumer characteristics, the number of competing EDs, and the size of the market. The Salop model directly implies that $\partial V/\partial N < 0$; at the same time, changes in N with a fixed m relaxes the constraint at which patients use emergency care. The effect of m on the number of visits is unclear: a larger m implies a larger market for an ED but increases competition by increasing the number of EDs in the market.

N changes according to the number of entries E and exits X of EDs. I use distance among EDs to identify entry and exit of competing EDs of incumbent ED i. Let $\mathbb{A}_i^m$ be the area of a circle of radius m around incumbent ED i. The set $\mathbb{O}_{it}^m \subset \mathbb{A}_i^m$ denotes the set of

EDs in $\mathbb{A}_i^m$ that are open in time t. Hence, the sets of entrant and exiting EDs j in area $\mathbb{A}_i^m$ are, respectively:

$$\mathbb{E}_{it}^m = \{j: j \notin \mathbb{O}_{it-1}^m \wedge j \in \mathbb{O}_{it1}^m\}$$

$$\mathbb{X}_{it}^m = \{j: j \in \mathbb{O}_{it-1}^m \wedge j \notin \mathbb{O}_{it1}^m\}$$

The number of competing EDs of incumbent ED at a radius m in time t is given by

$$N_{it}^m: |\mathbb{O}_{it}^m| = |\mathbb{E}_{it}^m| - |\mathbb{X}_{it}^m| + N_{it-1}^m$$

$$N_{it}^m = E_{it}^m - X_{it}^m + N_{it-1}^m \tag{5}$$

Methods

Without defined functional forms for $Q(\cdot)$, I estimate the number of visits of ED i at a radius m in time t by a linear approximation of (4) combined with (5):

$$V_{it} = Z_{it}'\beta + \delta_1^m E_{it}^m + \delta_2^m X_{it}^m + \delta_3^m N_{it-1}^m + \lambda_t + \eta_i + \varepsilon_{it} \tag{6}$$

where Z_{it} is a set of consumer and market characteristics that shift demand and costs, N_{it}^m is the number of competing EDs in a circle of radius m, λ_t controls for any underlying trend in emergency services utilization, η_i captures time-invariant characteristics of ED i, and ε_{it} includes unobserved time-varying characteristics that affect the number of visits. By the Salop model and *(5)*, $\delta_1 < 0$ and $\delta_2 > 0$ as ED entries (exits) increase (decrease) competition and decrease (increase) visits for ED i, respectively. Parameter δ_3 indicates the effect of lagged competition on visits, and it is expected to be non-positive. δ_1 and δ_2 are contemporaneous effects of ED entry and exit on visits, and δ_3 is the effect on subsequent number of visits of both entry and exit (a negative effect if entry, and a positive effect if exit). The role of m in (6) comes at a trade-off: a larger m implies a higher N^m and therefore potentially higher E^m and X^m, but the marginal ED competitor has a smaller effect on visits.

Equation (6) can be estimated with a fixed effects (FE) model. This model is equivalent to a difference-in-differences model with several time periods and treatments (in our case, entry and exit of EDs) occurring at different time periods. However, the individual η_i effects may be random instead of fixed; then the appropriate way to estimate (6) is with a random effects (RE) model. I use a Mundlak test (Mundlak, 1978) to identify whether FE or RE are appropriate. The initial parameters of interest from equation (6) are $\{\delta_1, \delta_2, \delta_3\}$. A strict exogeneity assumption must be satisfied for these parameters to be estimated without bias (Wooldridge, 2002): given the fixed effect η_i, the error term ε_i and the independent variables Z_{it} and particularly $\{E_{it}, X_{it}, N_{it-1}\}$ are uncorrelated. However, entry and exit of EDs can be endogenous to visits: an ED with a high number of visits may signal to other competitors that there are positive profits in a certain geographic area, hence inducing ED entry. The variables Z_{it} may not capture unobserved economic conditions that simultaneously causes low visits and ED exits. I use an instrumental variable approach to correct for these sources of bias due to endogeneity of ED entry and exit. However, the results from this approach are *local*, in the sense that the estimates will show the effect of entry and exit on visits for those EDs for which the instruments induced the entry or exit (Angrist et al., 2012; Imbens et al., 1994). Larger standard errors and a less efficient estimation are other drawbacks from the IV estimation, as well.

My first instrument follows the literature of hospital entry and competition (Abraham et al., 2007). I use the Land and Property Value price index calculated by the Lincoln Institute of Land Policy (Davis & Palumbo, 2008; Davis et al., 2007; Davis, Lehnert, et al., 2008). This index tracks the changes in land prices for all states, Washington DC, and 46 Metropolitan Statistical Areas (MSAs) The index is calculated at the state and metropolitan area levels; I use population weights to extrapolate to the county level. The identifying assumption for this instrument is that changes in land prices change the cost of opening EDs and the opportunity cost of leaving EDs open, but do not directly affect visits after controlling for other demand shifters. The second instrument follows the literature that assesses peer effects (Mora et al., 2013), a strategy that can be summarized by the phrase "the friends of my friends that are *not* my friends." For an ED i with neighbors (open or closed) EDs j, I use the aggregate visits of EDs k that are neighbors of EDs j but are *not* neighbors of ED i. The identifying assumption for this instrument is that the market conditions of EDs k, summarized in their number of visits, are correlated with the number of visits of EDs j but not with the number of visits of ED i . I test for the validity (over-identification, weakness, and endogeneity of instrumented variables) of both instruments.

Data and descriptive statistics

The main data source for this dissertation is the National Emergency Departments Inventory (NEDI-USA), a survey undertaken by the Emergency Medicine Network at the Massachusetts General Hospital (Sullivan et al., 2015). The NEDI-USA compendium has information of all EDs in the United States, biennially from 2001 to 2013 (plus an additional round of surveys in 2012). Although the dataset has information on federal hospital EDs (Army, Navy, Veteran Affairs, etc.) and specialty hospital EDs (psychiatric, chemical dependency, etc.), I focus on EDs that attend to general emergency patients and are available to the public. In particular, the dataset has information on ED characteristics and the hospitals with which they are affiliated (critical access, academic, freestanding, trauma level, etc.), the yearly number of visits per year, and geographical location (rurality, latitude and longitude). In addition, the NEDI-USA dataset includes an indicator for whether the ED is in operation, or if the ED opened or closed between each survey. For FSEDs, NEDI-USA compiles information on FSEDs' parent hospital. The definition of an FSED is not standard across states (Herscovici et al., 2020), but in the NEDI-USA data is defined as a multi-specialty EDs, open 24 hours a day and 7 days a week, that is affiliated to a hospital but not physically attached to it. These data have been used in other publications related to emergency services utilization (Freeman et al., 2020; Herscovici et al., 2020; Muelleman et al., 2010; Patidar et al., 2016, 2017b; Sullivan et al., 2012).

TABLES AND FIGURES

Table *1* shows the basic descriptive statistics of the EDs and FSEDs used in this dissertation, from 2005 and 2013. The number of hospital-based EDs decreased slightly between 2005 and 2013; this decline is concentrated in rural and non-metropolitan areas. These numbers follow the trend in hospitals closures seen since 2005 (The Cecil G Sheps Center for Health Services Research at the University of North Carolina, 2021). The number of metropolitan hospital-based EDs increased 4.2 percent during the period. Despite these decreases in the number of hospital-based EDs, the total number of visits has increased across the board in hospital-based EDs in any location. The number of FSEDs increased by 192.7 percent between 2005 and 2013.

Despite the small decrease in hospital-based EDs, the number of visits at these locations between 2005 and 2013 increased by 19.3 percent in EDs in all areas, and by 23.3 percent in metropolitan areas. The number of visits in rural EDs shows a moderate increase from 2005 to 2012 and a sharp decrease in 2013, for a net increase of 2 percent during the period. There is also an increase in concentration of hospital-based EDs visits in metropolitan areas, from 81.3 percent in 2005 to 84.1 percent in 2013. The number of visits in FSEDs increased by 200.1 percent between 2005 and 2013. Figure 1 shows the regional distribution of FSEDs in 2005 and 2013. Most FSEDs are located in metropolitan areas. Growth in the number of FSEDs is concentrated in six states (Texas, Ohio, Florida, Maryland, and Michigan), while North Carolina, Illinois, Kentucky, Colorado, and Washington saw larger increases in visits than other states (Figure 2).

In addition to the NEDI-USA data, I use information from the 2005-2013 Small Area Health Insurance Estimates and Small Area Income and Poverty Estimates programs from the US Census Bureau as county-level demand shifters. In particular, I use population, number of people in poverty, median household income, and number of people without health insurance to control for individual characteristics that influence the demand for emergency services. Previous literature has found that primary care (Billings et al., 2000a), and care provided at medical homes (David et al., 2015), urgent care clinics (Weinick et al., 2010), and retail clinics (D. Alexander et al., 2017; Mehrotra et al., 2008) are imperfect substitutes of emergency services. To capture the influence of health care that may substitute for emergency services, I use the Area Resource Health Files (AHRF) to obtain the number of primary care physicians and physician assistants per county.

Results

Figure 3 shows the distribution of the distance from an ED to the closest neighbor ED in 2013, the last year of the sample. The median distance from an open ED to the closest open neighbor is 9.4 miles. Because urban areas are denser, the distance between EDs is shorter: a median distance of 3.8 miles in metropolitan areas, while the median distance of EDs in rural areas is 17.1 miles. These results have several implications for the choice of m in the estimation of (6): for some EDs, a sufficiently small m yields $\mathbb{O}_i^m = \{\emptyset\}$ and therefore there is no entry or exit. This sufficiently small m is larger for EDs located in rural areas than for EDs in metropolitan areas. At the same time, the competition effect of the additional EDs included due to a larger m is smaller. As a result, I expect differential effects of ED entry and exit, where EDs in located in rural areas have smaller effects for both reasons (less competition and smaller competition effects). I estimate (6) for m from 2 to 30 miles (the approximate 95$^{\text{th}}$ percentile of the distance to the closest ED).

Figure 4 shows the average number of EDs in areas of radius of 2, 16, and 30 miles (values that correspond to the extremes and the midpoint of the distance distribution) around all EDs and metropolitan EDs. EDs located in urban areas have more neighbors than those in rural areas. When the area around an ED increases, the number of neighbors increases: the average number of neighbors is 0.39 at a 2-mile radius, 6.9 at a 16-mile radius, and 16 at a 30-mile radius. There is a slight decrease in number of neighbors over time at all radii and ED location, but the year-to-year variance is small.

Figure 5 and Figure *6* focus on entrants and exits in the surrounding areas of incumbent EDs. Figure 5 shows the percentage of EDs with an entrant or exit in its surrounding area. As before, larger areas have more EDs with entrants and exits, and EDs located in urban areas are more likely to have an entrant or exit in their surrounding area. EDs with entrants are more prevalent in earlier years than EDs with exits, but this situation is reversed in later years, indicating an increase in exits. Figure 6 reinforces this result: the average number of entrants per ED is higher than the number of exits in the first years of the sample, but exits exceed entrants in the latter years of the study period. These figures evidence that ED entries and exits are concentrated in metropolitan areas; for this reason, I'll focus my results on all EDs and metropolitan EDs only.

Table 2 through Table *5* show the results of estimating (6) using Ordinary Least Squares (OLS) for all (Table 2 and Table 3) and metropolitan (Table 4 and Table 5) EDs and for different calculations of the area surrounding each ED. Following **Error! Reference source not found.**, I select values of m close to the median distance to the closest ED, by ED location. Additionally, I add interactions to the measures of ED entrance and exit: miles between ED and the entrant or exiting ED, and the lagged volume of the exiting ED. If there are no entrant or exiting EDs, these interacting variables take the value of zero. The Mundlak test results favor fixed over random η_i, so I use a FE model to estimate (6). The multivariate model includes control variables for demand and cost shifters measured at the county level: population, population in poverty, median household income, population not insured, number of primary care physicians (PCP), and the number of physician assistants (PA).

In general, OLS results show differential effects of entry and exit of EDs and competition on visits (*Table 2*). For the average ED, an additional entrant within a 2-mile radius decreases the contemporaneous number of visits of the incumbent ED by 2,951 patients ($\widehat{\delta_1}$; 11.3% of mean number of visits) and decreases the number of visits in subsequent periods by 2,965 patients ($\widehat{\delta_3}$; 11.4% of mean number of visits). In the case of an additional ED exit in the same 2-mile radius area, the contemporaneous number of visits increases by 2,189 ($\widehat{\delta_2}$; 8.4% of mean number of visits), and in subsequent periods increases by 2,965 patients $\left(-\widehat{\delta_3}\right)$. In models estimated with data from larger surrounding areas (i.e. with larger m), the contemporaneous effect becomes not statistically significant, and the subsequent effect remains significant and negative but is smaller in magnitude. Regardless of statistical significance, the effect of ED exit on the number of visits remains positive as the surrounding area increases, but the effect of ED entry changes from negative to positive; this unexpected result could be explained by the possible bias introduced by the endogeneity of ED entry. The interactions (*Table 3*) are not statistically significant in general due to low variation as the interacting variables are not defined for incumbent EDs without an entry or exit.

The results for metropolitan EDs (*Table 4*) show statistically significant subsequent effects of ED entry and exit, but the contemporaneous effects are statistically significant only in small surrounding areas. An additional entrant within a 2-mile radius, on average, decreases the contemporaneous number of visits of the incumbent ED by 2,739 patients and decreases visits in subsequent periods by 2,669 patients. In the case of an additional ED exit in the same 2-mile radius area, the contemporaneous number of visits increases on average 2,249 visits, and in subsequent periods increases by 2,69 visits. The contemporaneous effect coefficients are not statistically significant at radii greater than 4 miles. As with all EDs, the contemporaneous effect of ED entry is larger than of exit. The results from interacted model (*Table 5*) are not distinctly different than those from the main model.

Table 6 and *Table 7* show the results of estimating (6) with instrumental variables and generalized method of moments. I estimate these models using a generalized method of moments with fixed effects for EDs and clustered standard errors at the ED level. For the instrumental variable estimations to be valid, instruments should be relevant (strongly correlated with the endogenous variables) and excluded (uncorrelated with the dependent variable, conditional on the endogenous and exogenous variables). I run statistical tests to assess the relevance of the instruments; the exclusion restriction is empirically untestable, but an over-identification test in a model with more excluded instruments than endogenous variables sheds light over this assumption. Since the model has two endogenous variables (number of entrants and exits) and there are three excluded instrumental variables (the aggregate volume of the neighbors of the incumbent ED's neighbors, the aggregate volume of the neighbors of the incumbent ED's *closed* neighbors, and a land price index), I'm able to run over- and under-identification tests.

The tests of instrument validity in the first stage of the estimation support the hypothesis of valid instruments in all estimations. The Sandersons-Windmeijer F tests reject the joint hypothesis of the instruments not correlated with the endogenous variables in the two first-stage equations (Sanderson et al., 2016). The Kleinbergen-Paap Wald F statistic tests for weak identification with clustered standard errors, but there are no defined critical values to reject the hypothesis of weak identification (Kleibergen et al., 2006). The values of this F statistic are relatively large for the estimation of the model for all EDs. In a similar fashion, the under-identification test of the Kleinbergen-Paap rk chi-squared statistic rejects the under-identification hypothesis for all EDs. The non-rejection of the hypothesis of the Sargan-Hansen statistic also gives credibility to the instruments, in particular to the exclusion restriction assumption described before (Bhargava, 1991). Overall, the instruments are relevant and not weak.

Table 6 shows the IV estimation results for all EDs. At $m = 10$ miles, an additional ED entrant decreases the number of visits on average 6,058 visits contemporaneously and 1,147 visits subsequently, while an ED exit increases the number of visits on average 784 visits contemporaneously and 1,147 visits subsequently. Compared to the OLS results, the contemporaneous effects of entry and exit are mostly not statistically significant at all radii, but the subsequent effect is still statistically significant and negative. This result could indicate that consumers take time to adapt to changes in the accessibility of ED services. However, even if the coefficients of the concurrent effects are not statistically significant, they have the expected signs. The relevant IV coefficients are larger than those from the OLS regressions; this suggests that the OLS estimates are biased whereas the IV estimates are not, or that the IV estimates are local effects. In the estimates for EDs in metropolitan areas (Table 7), the statistical significance of the subsequent effects is also lost for some of the different surrounding areas.

Discussion

My results support the premise of geographical competition in emergency services. Entry or exit of EDs in the neighboring region of an incumbent ED change the number of visits in the incumbent ED. When ED entry or exit happen further away from the incumbent ED (operationalized in my models as a larger radius around the incumbent ED), the changes in visits at the incumbent ED are smaller. These results are driven by EDs located in urban areas; as very few ED entry and exit occur in rural areas, my results are not granular enough to support any hypothesis of geographic competition.

Two main topics arise from the results of the estimation. First, the geographical competition effects are not symmetrical: ED entry is associated with larger decreases in visits at the incumbent ED than those associated with ED exits. This asymmetry could be a result of scale: closing firms tend to be smaller (Agarwal et al., 1996), so the number of visits diverted from the closed ED to the incumbent ED is relatively lower. At the same time, entering EDs can be small too. In my data, the number of visits of entering EDs is about 5.5 percent (1,423 patients on average) lower than incumbent EDs, and the number of visits of exiting EDs in the period before exit is about 6.1 percent (1,557 patients on average) lower than incumbent EDs. Second, changes in visits occur mostly in periods *after* ED entry or exit. The contemporaneous effects of entry and exit are statistically significant mostly in small surrounding areas, while subsequent effects are consistently statistically significant across specifications. These results may indicate path dependence in the emergency services market, where patients are slow to react to ED entry and exit due to previous decisions to use the incumbent EDs. Path dependence implies a learning behavior from patients, where other factors besides ED location are involved in the decision to use a particular ED. In the following Chapter I test whether these changes in emergency services availability are associated with health outcomes.

The analysis in this chapter has several potential limitations. First, the data available do not have information of individual ED installed capacity or utilization. If hospitals invest to increase ED installed capacity, or if the level of ED utilization varies, and this information is unknown, then the econometric estimation of (6) is biased. However, if installed capacity and utilization are characteristics that change gradually, most of this information would be captured by the ED fixed effects. A related limitation is the lack of data on individual patients instead of aggregate visits. With individual patient data, a more nuanced analysis of discrete choice is more informative about how patients decide to use emergency services when EDs enter or leave a market. Lastly, the study lacks an economic model of ED entry and exit that allows me relax some assumptions of the traditional Salop model (geographic and scale homogeneous firms). With such model I could simulate the effects of ED entry and exit on the number of visits by changing exogenous factors of entry and exit, such as Certificate of Need policies or public health insurance expansions.

CHAPTER 2. AGGREGATION OF VISITS AND ITS ASSOCIATION WITH MORTALITY

Analytical framework

Results from the previous chapter show that geographic competition in the emergency services exists, as a recently opened ED reduces the number of visits of incumbent EDs, and a recently closed ED increases the number of visits of incumbent EDs. However, this information is not sufficient to test induced demand. For instance, an ED closure increases visits at incumbent open EDs nearby. But perhaps some patients decide or are not able to seek care at nearby EDs; these patients are not captured in the results from equation (6). To test for induced demand, I make a prediction of market-aggregated visits gained or lost after changes in the availability of EDs. I use equation (6) from the previous chapter to estimate the counterfactual number of visits for incumbent EDs as if entry and exit of EDs had not happened. I also use equation (6) to estimate the counterfactual number of visits of closed EDs as if they were still open. The predicted change in visits due to entry and exit of EDs in market H at the end of time period t is given by

$$L_{Ht} = \sum_{j \in \{\mathbb{E}_{Ht}, \mathbb{X}_{Ht}\}} \left[\widehat{V_{jt}} - \sum_{i} \left(\widehat{V_{it}}(N_{it}) - \widehat{V_{it}}(N_{it} = N_{it-1}) \right) \right] \tag{7}$$

L_{Ht} is the difference between the counterfactual volume of recently opened or closed EDs $\widehat{V_{Jt}}$ in market H and the difference between the counterfactual volume of incumbent EDs with ED entry or exit in their vicinity $\widehat{V_{it}}(N_{it})$ and the number of visits without any changes in competition $\widehat{V_{it}}(N_{it} = N_{it-1})$. The summation inside the squared brackets in (7) accounts for the aggregate change in visits in incumbent EDs due to entry and exit. The difference between this summation and the counterfactual volume of new or closed EDs indicates visits that were created by an entry or that disappeared from an exit; that is, the number of visits that was not diverted to or from incumbent EDs.

Methods

To test for induced demand, I estimate a Poisson regression at the market level with emergency-related health outcomes R_{Ht} as dependent variables and L_{Ht} as the main explanatory variables. The Poisson model with a dependent count variable R_{Ht} has a conditional expectation given by:

$$\log\left(E(R_{Ht}|Z_{Ht}, L_{Ht}, \xi_t)\right) = Z'_{Ht}\gamma + \phi L_{Ht} + log\ P_{Ht} + \xi_t + \kappa_H \qquad (8)$$

Where Z_{Ht} are characteristics at the county level, ξ_t are time fixed effects, and κ_H are fixed or random market effects distributed as a log gamma variable with mean 1 and variance α. The addition of the log of the population in hundred thousands (log P_{Ht}) and a restriction to the corresponding coefficient to 1 makes the estimated coefficients in this model interpretable as changes in mortality rates per hundred thousand. The hypothesis $H_0: \hat{\phi} = 0$ states that the net change in visits is not correlated with changes in health outcomes and implies that this change is a result of demand induced by the availability of emergency services.

There is evidence of race and sex disparities in access to emergency services (Hanchate et al., 2019; Parmar et al., 2018; Sarkar et al., 2020), so entry and exit of EDs could have differential effects on mortality rates by gender and race. In order to test if there are differential effects of changes of the availability of emergency services, I estimate equation (8) for mortality rates by sex (Male and Female) and race (White and Non-white).

Results from volume aggregation

I use the results from the OLS and IV models as inputs to equation (7) to predict the number of visits gained or lost due to ED entry and exit. For each new ED or closed ED, I use the estimates from (6) to compute an estimated number of visits and compare it to the change in estimated number of visits of the open EDs in the surrounding area. I aggregate the difference in visits at the county level; because county boundaries are arbitrary, visits from EDs located near these boundaries could be misallocated to a wrong county. This could bias the predicted results if there is a disproportionate number of EDs near county boundaries, but there is no plausible argument for such location bias. I calculate the predicted change in visits using the basic OLS estimates (*Figure 7*), the OLS estimates with interactions (*Figure 8*), and the IV estimates (*Figure 9*). It is worth noting that, since the instrumental variable results are estimates of local effects for an unknown subset of EDs, changes in visits based on these results will not reflect the changes for the whole population of EDs.

Figure 7 and Figure *8* show that ED entry creates more visits than the visits lost due to ED exit; between 2005 and 2013, ED entry created approximately 36 million ED visits (4.7 percent of total ED visits), and ED exit eliminated between 4 and 14 million ED visits (0.6-2.0 percent). The average number of patients gained per county-year is between 1,885 and 2,123, and between 203 and 800 patients are lost. Consistent with the results tables described before, aggregations made with results from wider areas result in smaller aggregate visits; aggregations calculated with the results of the models with interactions are similar to the ones calculated from the models without interactions. These results imply that most patients reallocate to neighboring EDs after an ED exits, but an ED entry reduces the number of visits in the neighboring EDs and increases overall utilization. The results from the IV model (Figure 9) show negative predicted volumes in some years for radii greater than 6 miles: the number of visits of ED entrants was less that the total decrease in visits at incumbent EDs, and the counterfactual visits of closed EDs was less than the total increase in visits at incumbent EDs. Negative predicted volumes are expected given the large magnitude of the IV coefficients of (6) and the extrapolation of local estimates into predicted aggregated visits.

Mortality rates results

I estimate equation (8) using Poisson regressions, where R_{Ht} is the number of deaths at time t in county H caused by conditions sensitive to emergency services, in three groups: heart related (ICD-10-CM I26-I28 ischemic heart disease, ICD-10-CM I26-I28 pulmonary heart disease, ICD-10-CM I30-I51 other forms of heart disease, and ICD-10 I60-I69 cerebrovascular disease), accidental (ICD-10-CM V01-V99 transport accidents and ICD-10-CM W00-X59 other external causes of injuries), and respiratory related (ICD-10-CM J40-J47 chronic lower respiratory diseases); of these conditions, I expect a stronger effect from the second group, as preventative care can influence cardiac and respiratory related mortality. Z_{Ht} are control variables that shift demand and cost for emergency services as described in the previous chapter. The coefficient of the log of the population (in hundred thousands) is restricted to 1, so that the estimated coefficients are changes in mortality rates per hundred thousand. Additionally, I include the total number of visits of emergency services to control for market size, and an indicator for when the number of deaths per county is small and the CDC considers the mortality rate as unreliable. I assumed κ_H market effects are random, as information on mortality is available for a sample of counties.

Table 8 and *Table 9* show the estimation of equation (8) for heart-related conditions, using the basic OLS and IV visits aggregation, respectively. Coefficients are reported in exponentiated form; a coefficient of 1.01 implies a 1 percent increase associated with a one unit increase in the corresponding variable, and the testable hypothesis of induced demand is $\widetilde{H_0}: e^{\widehat{\Phi}} = 1$. Results show a statistically significant correlation between visits lost and an increase in heart-related mortality rates. The results from the accident-related mortality rates (Table 10 and Table 11) don't show any statistically significant correlation between visits gained or lost and mortality, while the results from respiratory-related conditions (Table 12 and Table 13) show a statistically significant relationship between volume gained and a reduction in mortality. Aggregating visits using the basic

OLS model or the IV model doesn't change the results with respect to mortality changes, except for heart-related conditions, where IV visit aggregates have a positive correlation with mortality. Results are consistent for different aggregation areas, except for the smallest area (m=2), where visits gained is positively corelated with increases in mortality rates for heart-related and respiratory-related conditions. In general, the statistically significant correlations are small: an increase in 1,000 patients lost is associated with an increase in heart-related mortality rates of between 0.03 and 0.06 percent. Some coefficients of the visits gained don't have the expected direction, but the magnitude of the associations and the general lack of statistical significance do not contradict the expected results of the model.

Table 14 to Table *19* show the estimation of ϕ_1 and ϕ_2 from Equation (8) for male, female, white, and non-white mortality rates for heart-related conditions, accident-related deaths, and respiratory-related conditions, with OLS and IV visit aggregations. There is no solid evidence of differences in the correlations between changes in the number of visits and mortality by sex or race.

Discussion

The association between ED entry and exit and emergency-related mortality rates is ambiguous and varies by condition. First, some conditions are more sensitive to changes in visits due to ED entry or exit. Despite all conditions studied are sensitive to emergency services, mortality rates for heart- and respiratory-related conditions respond to changes to visits due to ED entry or exit, but mortality rates for accidents do not. While the first two conditions are also sensitive to preventative care outside the emergency department, transport accidents and severe external injuries are treated mostly in the ED. These results suggest that the demand-inducing hypothesis of ED entry and exit applies mostly to conditions that can only be treated in emergency departments. Second, despite some evidence of increases in mortality rates for heart-related conditions associated with the loss of visits due to ED exits, the small magnitude of this association puts in doubt the relevance of ED access to mortality. Overall mortality rates have declined at a yearly rate of about 1-1.5 percent since the mid 20th century (Cutler et al., 2001), and early medical (sulfa drugs in Jayachandran et al., 2010) and public health interventions (clean water technologies in Cutler et al., 2005) have reduced mortality rates between 2 and 12.9 percentage points, respectively. Under this light, estimated increases in heart-related mortality rates of 0.02-0.06 percent due to reductions in the number of visits are about one tenth of the decreases in mortality rates estimated for successful medical interventions. These results are in line with the literature on the subject, where ED closures are associated with worse health outcomes (Buchmueller et al., 2006; Lee et al., 2007; Liu et al., 2014). However, the lack of solid evidence regarding the association between increases in visits due to ED entry and mortality rates reinforces the previous results of asymmetric effects of ED entry versus ED exit.

CHAPTER 3. INPATIENT RISK SELECTION AND GEOGRAPHIC COMPETITION FROM FREESTANDING EMERGENCY DEPARTMENTS

Analytical framework

Increased competition in hospital markets, defined as more hospitals providing specialized services in a given market, is generally welfare-enhancing (Dranove et al., 1992; Kessler et al., 2000). However, when facing patients of different levels of acuity unknown ex-ante by the provider, certain reimbursement methods may provide incentives for hospitals to select patients by acuity level, and competition does not maximize social welfare. In particular, under a prospective payment system, where hospitals receive a fixed, predetermined amount per patient, hospitals have the incentive to *cream* (overprovide services to low acuity patients) and to *skimp* (underprovide services to high acuity patients) at the intensive margin (that is, on how much treatment to provide) (R P Ellis, 1998). These behaviors have equivalents at the extensive margin (that is, on which patients to treat), where providers prefer to treat low acuity patients, or to avoid high acuity patients. There is evidence that hospitals prefer low acuity patients, even if there is no consensus on whether low acuity patients are inherently more profitable (Friesner et al., 2009). Another instance where hospitals can select patients is through skimping low-income or uncompensated care patients. Uncompensated care costs in community hospitals accounted to US$38.4 billion dollars in 2017 (American Hospital Association, 2019), and an additional uncompensated patient costs hospitals approximately $800 per year (Garthwaite et al., 2018).

As cited in the introduction, previous studies show that FSEDs are located in more affluent areas. It is not clear if hospitals open FSEDs in affluent areas to attract advantageous patient types in the emergency care market or the inpatient care market. In the emergency care market, evidence shows that FSED entrance does not systematically change incumbent hospital-based EDs patient volume or quality of care (Xu et al., 2020). However, it is unclear whether FSEDs compete for admitted patients: I analyze whether hospitals with an FSED nearby have lower inpatient volume than hospitals that don't have an FSED nearby, and if this volume is higher in hospitals that opened an FSED. I analyze creaming and skimping behavior of FSED entrance in incumbent hospitals by estimating the change in case and payer mix in hospitals that faced an FSED opening in their vicinity, and in hospitals that opened an FSED. If hospitals use FSEDs to compete for good patient types, creaming/skimping behavior on the extensive margin would show that, all else equal, hospitals with an FSED nearby have patient population with higher acuity and a higher proportion of low-income patients than hospitals without an FSED nearby. For hospitals that opened an FSED, this behavior would show a patient population with lower acuity and a lower proportion of low-income patients than those that didn't open an FSED. On the other hand, hospitals may use FSEDs to seek high-risk patients that command higher reimbursements from the prospective payment system. As hospitals have more control over their own cost structure, higher reimbursement patients have the potential to become more profitable patients. Under this revenue-increasing hypothesis, hospitals with an FSED nearby have a patient population with a *lower* acuity than hospitals without an FSED nearby, and hospitals that opened an FSED have patient population with higher acuity than those that didn't open an FSED.

Data

In addition to the NEDI-USA data described previously, in this chapter I use data on hospital case and payer mix from the Center for Medicare and Medicaid Services (CMS) Acute Inpatient Prospective Payment System (IPPS). The IPPS program pays hospitals' operating costs for Medicare Part A inpatient admissions based on prospective, flat rates. These rates are calculated by categorizing observed cases into groups of similar resource utilization level (Diagnosed-Related Groups, DRGs), and assigning a weight to each DRG based on the average resource utilization to treat patients within the corresponding DRG; rates are adjusted by hospital, based on cost of living, academic status of the hospital, the percent of uncompensated care patients, and the presence of unusually expensive patients.

To calculate the base prospective inpatient rates to be applied in fiscal year $t + 1$, CMS calculates measures of case mix and disproportionate share of low-income patients in fiscal year t using Medicare Fee-For-Service administrative claims from fiscal year $t - 1$; that is, the data published in the final rule IPPS impact files of fiscal year 2015 are matched with the NEDI-USA data of 2013. From these impact files, I use the number of cases adjusted for transfers (CASETA), a case mix index (CMI) and a transfer-adjusted case mix (TACMI), and the disproportionate share of low-income patients (DSHPT) per hospital. CASETA is a measure of admitted patients, where a higher number implies more inpatient cases. CMI and TACMI indices measure the level of acuity of the inpatient population at a hospital: a higher case mix index implies a patient population with higher acuity. Last, DSHPT is the sum of two components: inpatient days of Medicare patients in Supplemental Security Income program as a percent of inpatient days from all Medicare patients, and inpatient days of Medicaid-only patients as a percent of inpatient days from any payer. A higher DSHPT implies a higher low-income patient population.

I link this information from the IPPS Impact files for Fiscal Years 2007-2015 with the NEDI-USA geographical data to identify FSED openings within 6 miles from an incumbent hospital. This is the distance on MedPAC's recommendation for cuts in reimbursement rates for opening FSEDs. I check for robustness of the results with distances between 2 and 10 miles. I also link the data from the IPPS impact files and NEDI-USA data to identify which parent hospitals opened FSEDs. I use information from the 2005-2013 Small Area Health Insurance Estimates and Small Area Income and Poverty Estimates programs from the US Census Bureau to obtain county-level population over 65 years old, number of people in poverty, and median household income.

Table 20 shows the descriptive statistics of the sample used in this chapter. Of the distinct 3,970 hospitals in the IPPS data during the study period, 3,222 hospitals (81.2 percent) have a match in the NEDI-USA data. Approximately 67 percent of all matched hospitals are located in metropolitan areas, while only about 13 percent are located in rural areas. The sample includes few Critical Access hospitals (7 in 2005 but none by 2013). The number of hospitals that operate at least one FSED increased 184 percent between 2005 and 2013. In terms on characteristics of the area where FSEDs are located, much has been reported in the literature previously cited; it is not my intention to repeat or replicate those results, but to show the location of FSEDs as a mechanism to compete for inpatient admissions. About 75 percent of FSEDs are located in the same county as the parent hospital; if hospitals use FSEDs to compete for inpatient admissions or emergency care patients, this competition is mostly local. On average, a hospital has between 3,079 (in

2013) and 3,564 (in 2005) transfer-adjusted inpatient admissions in the IPPS. Both the Case Mix and Transfer-Adjusted Case Mix indices have trended upward in the study period, but the disproportionate share percent increased from 2005 to 2009 and remained constant from 2011 to 2013.

Methods

Equation (9) presents the econometric model I use to estimate the effect on a hospital's inpatient volume, case and payer mix of an FSED opening in the vicinity or a hospital opening an FSED.

$$C_{it} = X_{it}'\beta + \delta_m F_{it}^m + \theta O_{it} + \lambda_t + \gamma_i + \varepsilon_{it} \tag{9}$$

C_{it} is the volume, case mix or payer mix in hospital i at time t. X_{it} is a set of hospital and county characteristics: number of beds in hospital, county population 65 years old and older, population with income under the Federal poverty line, and median household income. λ_t is a set of year fixed effects that capture underlying trends in patient acuity, and ε_{it} is an error term that captures unobserved time-varying hospital characteristics that affect case or payer mix. As in previous chapters, I run Mundlak tests to determine if γ_i are fixed or random; these effects capture all information of observed and unobserved time-invariant hospital characteristics. The variables of interest are F_{it}^m as the number of FSEDs open within a m miles radius around hospital i at time t, and O_{it} as the number of FSEDs operated by hospital i at time t. Coefficient δ_m is the average difference in volume, case or payer mix between hospitals with an FSED within m miles and hospitals without FSEDs within m miles, and θ is the average difference in volume, case or payer mix between hospitals that operated one more FSED. When inpatient volume is the outcome of interest, a negative δ_m or a positive θ are evidence that FSEDs compete with incumbent hospitals for inpatient volume. A positive δ_m or a negative θ for the case mix and payer indices would support the hypothesis of creaming/skimping, while a negative δ_m or a positive θ would support the revenue-enhancing hypothesis.

FSED location or operating an FSED are not random: as described previously, the literature has found that hospitals locate FSED strategically in areas with higher expected revenue from more affluent, better insured patients. In a similar fashion, larger hospitals with better management are more likely to operate FSEDs (Patidar et al., 2017a). If so, OLS estimation of Equation (9) is biased because some unknown information in ε_{it} is correlated with the number of FSEDs in the vicinity or the likelihood of a hospital operating an FSED. I use an instrumental variable approach to correct for this potential bias. The first excluded instrument is the Land and Property Value price index calculated by the Lincoln Institute of Land Policy (Davis & Palumbo, 2008; Davis et al., 2007), described in Chapter 1. The identification assumption behind this instrument is that more expensive real estate increases the costs of opening an FSED but does not directly affect emergency care utilization, conditional on other observed time-variant characteristics and time and county fixed effects. I use the population-weighted land price index at time t of the county where hospital i is located and its neighboring counties, because most parent hospitals open their FSEDs in their county (67.9 – 76.5 percent). In addition, I include as instruments the number of hospital-based EDs within m miles of the incumbent hospital and the number of hospital-based EDs in the county and adjacent counties of the parent hospital. The identification assumption for these instruments is that a hospital is less likely to open an FSED in an area with more competition in emergency services, but that the increased competition of *hospital-based* EDs is not motivated by creaming or skimping. I estimate all instrumental variable models with a generalized method of moments.

Results

Figure 10 shows the percent of hospitals in the sample with an FSED within 2 to 10 miles. By 2013, less than 1 percent of hospitals have an FSED within 2 miles, but about 7 percent of hospitals have one within 10 miles. I expect a similar trade off as seen in Chapter 1, where a shorter radius has lower variability in the number of FSEDs but a closer FSED perhaps commands a stronger association with the model outcomes.

Table 21 shows the results of the OLS estimation of Equation (9) with a radius $m = 6$ miles, for hospitals in any location. As in Chapter 1, in all specifications the results from Mundlak tests favor a fixed γ_i. To ease the interpretation of the changes in outcomes associated with the number of FSEDs in the vicinity or the number of FSEDs operated, I include the percent change (in italics) and the 95% Confidence Interval of this percent change of the outcome variable associated with the estimated coefficient. There are no statistically significant changes in the number of transfer-adjusted cases (CASETA) associated with the presence of FSEDs within 6 miles, but there are statistically significant decreases of 7.9 (95% CI -13.11 , -2.84 in all hospitals) and 6.4 (95% CI -10.68 , -2.06 in hospitals in metropolitan areas) percent associated with operating an FSED. There are statistically significant increases in the case-mix (CMI) and the transfer-adjusted case-mix

(TACMI) associated with FSEDs: a hospital with an FSED within 6 miles has a CMI on average 1.763 percent (95% CI 0.48 , 3.05) higher and a TACMI 1.780 percent (95% CI 0.49 , 3.08) than a hospital without an FSED within 6 miles. These changes are slightly different in metropolitan hospitals (Table 22). The OLS results for payer mix contradict the hypothesis of creaming/skimping: another FSED within 6 miles is associated with a statistically significant decrease in the disproportionate share percent of 1.895 percent (95% CI -3.44 ; -0.35) of an average hospital, or 2.354 percent (95% CI -3.91 ; -0.80) of a metropolitan hospital. These results are robust to estimating Equation (9) with different radii (Table 23 and Table 24), except at radius $m = 2$ miles.

The results of the instrumental variable estimation of Equation (9) are in Table 25 (all hospitals) and Table 26 (metropolitan hospitals). These results consider the strategic decisions of hospitals to operate FSEDs and their location. The bottom of the table lists the tests of appropriateness of the instruments. The first stage tests for weak instruments (Sanderson-Windmeijer weak IV and Kleibergen-Paap under-identification tests) show a strong correlation between the instruments and the number of FSEDs nearby and the number of FSEDs operated in the first stage in all models. However, the Hansen J test of over-identifying restrictions rejects the hypothesis of the instruments being uncorrelated with the disproportionate share percent; this hypothesis is not rejected for the volume or the case mix outcomes.

The instrumental variables models show a statistically significant decrease in volume of 30.7 percent associated with an additional FSED within 6 miles, but not an increase in hospitals that operate FSEDs. For the case mix indices, there is an increase of 23.94 percent (95% CI 10.20 ; 37.68) in CMI and of 24.13 percent (95% CI 10.40 ; 37.86) in TACMI associated with hospitals operating an additional FSED. There's no statistically significant association between FSEDs within 6 miles and case mix. For areas of 8- and 10- mile radius, where Figure 4 shows more FSEDs included in the vicinity, FSEDs are associated with reductions in CMI and TACMI of between 6.102 and 5.988 (10-mile radius) and 8.959 and 8.754 (8-mile radius) respectively (Table 27 and Table 28). As before, these results are similar for hospitals in metropolitan areas. Estimates for FSEDs within 2- and 4-mile radius show that the instruments are weak at explaining the number of FSEDs in the area in the first stage of the instrumental variable models.

The results of the payer mix models deserve special attention. The Hansen tests reject the hypothesis of valid instruments, so the IV estimates of δ_m and θ do not correctly consider the endogeneity of FSED location and operation. As an *ad hoc* analysis, I estimate δ_m and θ separately using as instrument the land price index of the county where hospital i is located (for δ_m) or the population-weighted land price index of the county and adjacent counties where hospital i is located (for θ). These models are exactly identified, because there is only one excluded instrument per endogenous variable; thus, it is not possible test the exclusion condition in the second stage. Table 29 and Table *30* shows these results. The instrument is strong for 6- to 10-mile radius areas, but, despite low p-values for the Sanderson-Windmeijer Weak Identification and Kleibergen-Paap Underidentification tests, not very strong for the number of FSEDs operated or 2- and 4-mile radius areas. There are strong and large increases in the disproportionate share percent associated with the number of FSEDs, from 78.23 to 131.2 percent in all hospitals, or from 51.67 to 85.41 on hospitals in metropolitan areas. The reduction in the disproportionate share percent associated with operating FSEDs is large (91.27 percent), but only statistically significant at 90%.

Discussion

The rapid expansion of FSEDs in the last decade has been advertised as an opportunity to improve the provision of emergency services, alleviating overcrowded emergency rooms, and expanding access to emergency care (Baehr et al., 2020b; Harish et al., 2016). However, given that this expansion has occurred in geographical areas where there is no apparent need for more emergency care providers (A. J. Alexander et al., 2019; Dark et al., 2017; Patidar et al., 2016), FSEDs are not seen as benevolent by some. Evidence to date shows that FSEDs do not alleviate overcrowding in hospital-based EDs and are associated with increases in private and public health care expenditures (Ho et al., 2017, 2019; Patidar et al., 2017b). Because EDs are a source of patients to a hospital (Morganti et al., 2013), FSEDs have the potential to attract patients from a different area where their parent hospitals are located. It is not clear if the strategic location of FSEDs attracts patients with less complex conditions. My results don't fully support the hypothesis of hospitals using FSEDs to select lower acuity or higher income patients. While the estimates of simple associations show that hospitals with FSEDs nearby have a patient population of higher acuity than hospitals that don't have an FSED nearby, estimates that correct for the endogeneous FSED location show the reverse: hospitals with an FSED nearby had *lower* case mix indices than hospitals without FSEDs nearby. The evidence for hospitals that opened FSEDs also contradicts the creaming/skimping hypothesis: these hospitals have higher case mix indices than hospitals that didn't open an FSED.

These results favor the hypothesis of revenue maximization. The design of the IPPS assigns higher reimbursements to hospitals with higher case mix indices, and the program includes a provision for additional reimbursement for hospitals with a higher proportion of low-income patients. It is not clear whether hospitals that open FSEDs to obtain higher reimbursements from the IPPS via patients with higher acuity. It is beyond the scope of my study to evaluate whether the IPPS creates incentives for hospitals to prefer high-acuity patients instead of low-acuity patients.

The evidence of FSEDs selecting better insured patients for their parent hospital is weak, because the main instrumental variable approach yields invalid instruments to answer this question. In the models where the excluded instrument is strong, the ad hoc analyses show large changes in payer mix in incumbent hospitals that support the creaming/skimping hypothesis. However, the model is exactly identified so I cannot test any over-identifying restriction. The reliability of the estimate depends exclusively on the assumption that the excluded instrument is correlated with payer mix only through the number of FSEDs in the area. More work is required in this area.

There are also limitations to the analysis on this chapter. My results only consider Medicare Fee-for-Services inpatient admissions through the IPPS. Hospitals may use FSEDs to select low acuity patients from commercially insured patients, or from patients enrolled in Medicare Advantage plans. However, because Medicare patients account for most inpatient admissions from the ED (Morganti et al., 2013), and Medicare Fee-for-Services account for about two thirds of all Medicare patients, using information of Medicare Fee-for-Services patients should provide a good picture of the effects of FSEDs on the inpatient care market. And second,

DISCUSSION

In this dissertation I analyze geographic competition of EDs in the form of changes in availability of emergency services via entry and exit of EDs, and the expansion of FSEDs. Within this approach, I study two overarching topics: demand for emergency services induced by the availability of emergency services, and risk selection in inpatient admissions.

On the first question, the results provide a limited support the hypothesis of induced demand. Whereas there is a sizeable association between visits lost and higher mortality rates for heart-relate conditions, ED entry and increases in the number of visits are not associated with decreases in mortality rates. My results support an asymmetric effect for ED entry and exit: ED exit reduces overall visits and increases certain subject-specific mortality rates, but ED entry is not associated with decreases in mortality rates. Moreover, ED entry and exit affect mortality rates for conditions that can be treated in places of service outside the ED, but don't affect the mortality rates of conditions treated only in the ED, such as transport accidents and severe injuries. The implications of this asymmetry pose hard challenges for policy: policymakers need to identify which areas where EDs must be protected to prevent exits, but also place restrictions to ED entry in areas where new entrants are not needed. Market interventions like Certificate of Needs must consider this asymmetry.

On the second question, my results support inpatient selection based on high-revenue patients instead of selection based on low-acuity patients. Even when considering the strategic location of FSEDs, the case mix of hospitals with FSEDs nearby is lower than in hospitals without FSEDs nearby, and the case mix of hospitals that operated FSEDs is higher than those that did not operate FSEDs. A normative evaluation of these results is not straightforward, as the net change in resource utilization is unknown: unlike the analysis in the first two chapters of this dissertation where visits are fungible and net effects can be calculated, case mix indices are not fungible and the decrease in case mix index at incumbent hospitals cannot be aggregated and compared to the increase in case mix indices at parent hospitals. Current studies that compare Medicare resource utilization between areas with FSEDs and areas without FSEDs attempt this normative evaluation (Patidar et al., 2017b) and finds higher Medicare costs in counties with FSEDs than in counties without FSEDs. However, this study includes both emergency care and inpatient costs and doesn't isolate the changes in expenditures from inpatient care.

This dissertation has two main limitations, additional to the limitations discussed at the end of each chapter. First, it doesn't address changes in access to EDs in rural areas; access to care in rural areas is a common and well-studied problem. In the first two chapters, the smaller scale and relative low numbers of rural EDs combined with the long distances between EDs and population center inherent to rural areas make the analysis of aggregate patient volumes underpowered, as shown by the small number of neighbors, entries and exits, and the insignificant effects of entry and exit. A more nuanced approach that connects detailed emergency services utilization with rural EDs is more appropriate to analyze the emergency services market in rural areas. In Chapter 3, as few FSEDs are located in rural areas also makes the analysis underpowered. Second, the instrumental variable approach is less efficient that alternative methods that control for endogeneity, and produces results only for those EDs that faced ED entry or exit (in Chapter 1) or hospitals that have FSEDs nearby or decide to open FSEDs (in Chapter 3) are driven by changes in the instruments. As a result of this particular problem of instrumental variable estimation, the instrumental variable results are not generalizable to the population of EDs or hospitals. This is a well-known caveat of instrumental variables, but other mechanisms used with observational data to overcome selection biases and endogeneity (vg. natural experiments or regression discontinuity design) estimate results that are not generalizable either. However, the statistical tests performed to assess the quality of the instrumental variable approach show that the instruments satisfy the basic requirements of validity on all models in Chapters 1 and most models (except on the payer mix models, as discussed previously) in Chapter 3.

CONCLUSIONS

This dissertation analyzes geographic competition of EDs and how it is related to health care utilization and health outcomes. In Chapter 1 I analyze how entry or exit of EDs changes the number of visits of incumbent EDs by diverting or attracting patients from the new or closed ED, and in Chapter 2 I analyze how these changes in visits are associated with changes in emergency-related mortality rates. Both questions try to answer whether the availability of EDs induces demand for emergency services. My results show differential effects of ED entry and exit: the decrease in visits at an incumbent ED resulting from increased competition through ED entry is higher than the increase in visits resulting from a decrease in competition through ED exit. Moreover, the effects of competition on the number of visits appear in the years following the ED entry and exit. These competition effects occur mostly in EDs located in metropolitan areas. When aggregated, the number of visits created by ED entry is more than twice the volume created by ED exits; this evidence points to a story where ED exits divert patients from closed EDs to incumbent EDs, but ED entry steals patients from incumbent EDs and increases the overall number of visits. However, these increases in visits due to ED entry are not correlated with decreases in emergency-related mortality rates; the volume of patients lost due to ED exits is correlated with small increases in heart-related mortality rates. These results support the hypothesis of induced demand for ED entry, but there is not enough evidence with regards to ED exit.

Chapter 3 analyzes how geographic competition of FSEDs, a relatively new development in emergency services that allows hospitals to provide emergency services in areas different from the main campus, is associated with the risk profile of inpatient admissions. I analyze how the presence of a FSED near an incumbent hospital or the operation of an FSED by a parent hospital is associated with case and payer mix indices from Medicare's Acute Inpatient Prospective Payment System. My results show that hospitals with an additional FSED within 8 miles have case mix indices approximately 8 percent lower than hospitals without an FSED nearby; this percent decreases as the area surrounding the incumbent hospital increases. Hospitals that operate an additional FSED have case mix indices between 22 and 24 percent higher than hospitals that did not operate an FSED. These results contradict the hypothesis that hospitals use FSEDs to select lower acuity patients, favoring revenue-maximizing behavior where hospitals that operate FSEDs seek higher acuity patients who command higher reimbursement rates. Evidence that hospitals use FSEDs to select higher income patients is weak, but it agrees with previous research that shows that FSEDs locate in areas with higher income populations.

TABLES AND FIGURES

Table 1. Descriptive statistics of hospital-based Emergency Departments and Freestanding Emergency Departments

	2005	2007	2009	2011	2012	2013
Number of hospital-based EDs	4,800	4,806	4,784	4,777	4,792	4,793
Metropolitan	2,781	2,792	2,774	2,771	2,789	2,898
Adjacent to metropolitan	1,144	1,141	1,139	1,138	1,134	1,071
Rural	875	873	871	868	869	824
Number of FSEDs	69	86	127	161	182	202
Metropolitan	60	79	119	153	174	194
Adjacent to metropolitan	8	6	7	7	7	6
Rural	1	1	1	1	1	2
Visits at hospital-based EDs (‘000)	113,566.5	118,027.7	123,719.7	130,510.8	132,953.4	135,525.0
Metropolitan	92,370.1	95,900.4	100,680.6	106,832.9	109,194.8	113,931.7
Adjacent to metropolitan	13,832.5	14,488.0	15,050.9	15,570.7	15,572.7	14,109.4
Rural	7,363.9	7,639.4	7,988.2	8,107.2	8,186.0	7,483.9
Visits at FSEDs (‘000)	1,312.3	1,612.7	2,322.4	3,059.1	3,616.7	3,938.2
Metropolitan	1,239.2	1,542.1	2,238.9	2,972.9	3,499.2	3,839.7
Adjacent to metropolitan	73.15	69.97	82.81	85.48	116.06	94.07
Rural	0.01	0.68	0.71	0.68	1.41	4.5

Source: NEDI-USA 2005-2013. ED: Emergency Department. FSED: Freestanding Emergency Department.

Table 2. Ordinary Least Squares estimates, All Emergency Departments.

	m=2	m=6	m=10	m=14	m=18
Entrant (δ_1)	-2,951***	-437.1	128.2	460.0**	370.0**
	(870.0)	(438.0)	(304.2)	(223.5)	(187.4)
Exit (δ_2)	2,189**	573.4	251.3	65.75	-22.59
	(897.2)	(351.2)	(187.2)	(159.8)	(143.6)
Lag N (δ_3)	-2,965***	-1,164***	-486.7***	-285.0**	-211.0**
	(879.5)	(285.0)	(170.6)	(124.9)	(92.12)
All population (‘000)	4.273	6.212	5.425	5.488	5.747
	(6.129)	(5.993)	(5.806)	(5.796)	(5.908)
Population in poverty (‘000)	5.988	4.536	4.582	4.989	4.505
	(4.183)	(4.143)	(4.045)	(4.092)	(4.154)
Median household income (‘000)	-121.3***	-124.8***	-129.3***	-130.0***	-130.6***
	(22.66)	(22.70)	(22.77)	(22.82)	(22.73)
Number of PCPs (‘0)	-13.92	-13.52	-10.85	-10.26	-9.591
	(8.749)	(8.802)	(8.686)	(8.657)	(8.659)
Number of PAs (‘0)	70.93***	61.45***	64.50***	65.24***	65.29***
	(22.25)	(21.71)	(20.55)	(20.05)	(20.81)
Population not insured (‘000)	12.33**	11.30**	11.56**	11.57**	11.63**
	(4.851)	(4.836)	(4.762)	(4.781)	(4.787)
Constant	22,247***	22,601***	22,531***	22,266***	22,145***
	(2,659)	(2,663)	(2,667)	(2,645)	(2,659)

	m=2	m=6	m=10	m=14	m=18
Time fixed effects	Y	Y	Y	Y	Y
Joint Mundlak Chi2 Stat.	368.93	354.53	312.76	280.2	276.03
Joint Mundlak Chi2 Stat. p-value	<0.001	<0.001	<0.001	<0.001	<0.001
Observations	29,578	29,578	29,578	29,578	29,578
R-squared	0.105	0.105	0.104	0.104	0.104
Number of EDs	5,209	5,209	5,209	5,209	5,209
Fraction of within variance	0.951	0.953	0.952	0.953	0.953
Corr(Z,η)	-0.494	-0.512	-0.504	-0.513	-0.523

Standard errors in parentheses, clustered at the ED level. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Ordinary Least Squares estimates with interactions, All Emergency Departments.

	m=2	m=6	m=10	m=14	m=18
Entrant (δ_1)	-2,818	-2,712***	-387.0	-311.2	178.2
	(1,832)	(927.9)	(593.6)	(574.9)	(395.4)
Entrant x Miles from entrant	-115.4	626.6**	82.75	88.16	17.85
	(1,399)	(265.6)	(82.86)	(60.43)	(31.94)
Exit (δ_2)	1,935	1,190	443.9	553.3	631.5
	(1,488)	(829.7)	(744.4)	(498.1)	(388.0)
Exit x Miles from closure	-166.5	-166.4	-5.796	-38.21	-38.76
	(982.4)	(194.9)	(100.7)	(54.15)	(30.96)
Exit x Volume closed	0.0166	-6.15e-05	-0.00216	-0.00203	-0.00289
	(0.0356)	(0.00592)	(0.00334)	(0.00194)	(0.00178)
Lag N (δ_3)	-2,987***	-1,200***	-487.2***	-280.2**	-191.2**
	(895.3)	(279.5)	(168.4)	(124.8)	(94.37)
All population (‘000)	4.402	6.149	5.355	5.388	5.479
	(6.139)	(5.932)	(5.733)	(5.763)	(5.869)
Population in poverty (‘000)	5.905	4.597	4.658	5.066	4.813
	(4.189)	(4.091)	(4.013)	(4.024)	(4.092)
Median household income (‘000)	-121.5***	-125.2***	-129.0***	-129.9***	-131.1***
	(22.65)	(22.62)	(22.77)	(22.76)	(22.67)
Number of PCPs (‘0)	-13.95	-13.61	-10.81	-10.55	-9.417
	(8.728)	(8.804)	(8.692)	(8.666)	(8.678)

	m=2	m=6	m=10	m=14	m=18
Number of PAs (‘0)	70.52***	60.44***	64.65***	65.21***	64.51***
	(22.21)	(21.50)	(20.33)	(19.86)	(20.77)
Population not insured (‘000)	12.22**	11.15**	11.48**	11.62**	11.82**
	(4.787)	(4.772)	(4.729)	(4.774)	(4.783)
Constant	22,250***	22,802***	22,576***	22,294***	22,032***
	(2,656)	(2,635)	(2,655)	(2,643)	(2,668)
Time fixed effects	Y	Y	Y	Y	Y
Observations	29,578	29,578	29,578	29,578	29,578
R-squared	0.105	0.106	0.104	0.105	0.105
Number of EDs	5,209	5,209	5,209	5,209	5,209
Fraction of within variance	0.952	0.953	0.952	0.952	0.953
Corr(Z,η)	-0.495	-0.505	-0.501	-0.509	-0.523

Standard errors in parentheses, clustered at the ED level. Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Ordinary Least Squares estimates, Metropolitan Emergency Departments.

	m=2	m=4	m=6	m=8	m=10
Entrant (δ_1)	-2,739***	-1,767***	-330.6	256.5	178.7
	(908.7)	(593.5)	(445.6)	(396.7)	(307.1)
Exit (δ_2)	2,249**	1,505**	559.7	402.7	265.6
	(965.1)	(594.7)	(353.2)	(275.1)	(187.1)
Lag N (δ_3)	-2,669***	-1,966***	-962.8***	-626.3***	-406.8**
	(936.9)	(502.6)	(288.0)	(213.1)	(171.2)
All population (‘000)	0.202	2.545	1.517	1.386	0.845
	(6.186)	(6.054)	(6.069)	(6.010)	(5.878)
Population in poverty (‘000)	0.709	-1.000	-0.252	-0.268	-0.206
	(4.223)	(4.166)	(4.178)	(4.141)	(4.072)
Median household income (‘000)	-118.0***	-123.6***	-124.2***	-129.6***	-131.3***
	(45.08)	(44.95)	(45.18)	(45.23)	(45.38)
Number of PCPs (‘0)	-20.52**	-21.31**	-20.18**	-18.54**	-17.94*
	(9.253)	(9.297)	(9.295)	(9.255)	(9.175)
Number of PAs (‘0)	34.90	27.13	28.35	30.03	30.81
	(23.90)	(22.90)	(23.29)	(22.88)	(22.07)
Population not insured (‘000)	13.33***	12.63**	12.57**	12.65***	12.82***
	(4.955)	(4.947)	(4.947)	(4.899)	(4.871)
Constant	34,709***	35,044***	35,402***	35,245***	35,342***
	(4,840)	(4,827)	(4,852)	(4,875)	(4,868)

	m=2	m=4	m=6	m=8	m=10
Time fixed effects	Y	Y	Y	Y	Y
Joint Mundlak Chi2 Stat.	82.85	84.64	72.94	62.62	55.16
Joint Mundlak Chi2 Stat. p-value	<0.001	<0.001	<0.001	<0.001	<0.001
Observations	16,083	16,083	16,083	16,083	16,083
R-squared	0.132	0.133	0.131	0.131	0.130
Number of EDs	2,920	2,920	2,920	2,920	2,920
Fraction of within variance	0.921	0.927	0.922	0.923	0.921
Corr(Z,η)	-0.400	-0.474	-0.419	-0.427	-0.405

Standard errors in parentheses, clustered at the ED level. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Ordinary Least Squares estimates with interactions, Metropolitan Emergency Departments.

	m=2	m=4	m=6	m=8	m=10
Entrant (δ_1)	-2,426	-2,963**	-2,532***	-1,552**	-330.4
	(1,904)	(1,234)	(951.9)	(732.5)	(605.6)
Entrant x Miles from entrant	-264.2	524.9	600.3**	359.4**	81.22
	(1,432)	(510.0)	(270.0)	(157.7)	(83.78)
Exit (δ_2)	2,299	1,324	1,376	755.2	664.7
	(1,647)	(1,205)	(871.4)	(718.9)	(777.3)
Exit x Miles from closure	-396.6	35.43	-215.9	-81.92	-33.47
	(1,075)	(450.1)	(202.0)	(121.4)	(104.9)
Exit x Volume closed	0.0146	0.00197	-0.000391	0.000851	-0.00275
	(0.0358)	(0.0117)	(0.00592)	(0.00418)	(0.00337)
Lag N (δ_3)	-2,683***	-1,963***	-1,001***	-652.0***	-406.0**
	(956.1)	(494.1)	(282.3)	(210.4)	(169.0)
All population (‘000)	0.304	2.538	1.483	1.388	0.840
	(6.190)	(5.928)	(6.007)	(5.906)	(5.797)
Population in poverty (‘000)	0.634	-0.924	-0.222	-0.523	-0.179
	(4.228)	(4.072)	(4.122)	(4.076)	(4.039)
Median household income (‘000)	-118.2***	-124.5***	-125.7***	-131.3***	-131.1***
	(45.07)	(44.95)	(44.98)	(45.13)	(45.37)
Number of PCPs (‘0)	-20.62**	-21.30**	-20.22**	-18.21**	-17.94*
	(9.232)	(9.291)	(9.303)	(9.256)	(9.175)

	m=2	m=4	m=6	m=8	m=10
Number of PAs (‘0)	34.63	26.80	27.23	28.73	30.82
	(23.85)	(22.85)	(23.10)	(22.65)	(21.83)
Population not insured (‘000)	13.25***	12.63***	12.43**	12.37**	12.71***
	(4.887)	(4.801)	(4.887)	(4.835)	(4.838)
Constant	34,720***	35,088***	35,766***	35,662***	35,406***
	(4,835)	(4,823)	(4,798)	(4,792)	(4,844)
Time fixed effects	Y	Y	Y	Y	Y
Observations	16,083	16,083	16,083	16,083	16,083
R-squared	0.132	0.133	0.132	0.132	0.131
Number of EDs	2,920	2,920	2,920	2,920	2,920
Fraction of within variance	0.921	0.927	0.922	0.922	0.921
Corr(Z,η)	-0.401	-0.474	-0.413	-0.419	-0.401

Standard errors in parentheses, clustered at the ED level. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Instrumental Variables estimates, All Emergency Departments.

	m=2	m=6	m=10	m=14	m=18
Entrant (δ_1)	-9,282	-6,044	-6,058*	-3,004**	-804.6
	(12,051)	(5,315)	(3,106)	(1,526)	(954.1)
Exit (δ_2)	27.04	2,203**	784.3*	412.6	12.56
	(2,880)	(1,111)	(440.2)	(309.0)	(270.6)
Lag N (δ_3)	-3,572	-2,344**	-1,147***	-654.9***	-311.5**
	(3,269)	(932.6)	(373.4)	(210.0)	(137.8)
All population (‘000)	4.909	10.77	10.79	11.07*	7.859
	(7.636)	(7.622)	(6.856)	(6.525)	(6.242)
Population in poverty (‘000)	5.078	-1.245	-6.204	-5.110	0.169
	(5.240)	(7.129)	(7.262)	(6.315)	(5.561)
Median household income (‘000)	-121.0***	-126.2***	-134.5***	-135.3***	-135.1***
	(22.36)	(22.53)	(22.76)	(23.00)	(23.14)
Number of PCPs (‘0)	-16.04*	-14.36	-11.62	-9.114	-10.50
	(8.917)	(8.848)	(8.786)	(8.669)	(8.547)
Number of PAs (‘0)	65.42**	41.94	35.42	39.22	56.70**
	(30.44)	(29.74)	(25.84)	(23.90)	(22.75)
Population not insured (‘000)	11.43**	9.092*	9.620*	8.871*	10.81**
	(5.362)	(5.307)	(5.009)	(4.976)	(4.840)
Time fixed effects	Y	Y	Y	Y	Y

	m=2	m=6	m=10	m=14	m=18
Observations	29,476	29,476	29,476	29,476	29,476
R-squared	0.097	0.083	0.040	0.067	0.098
Number of EDs	5,107	5,107	5,107	5,107	5,107
Sanderson-Windmeijer excluded Entrant F stat.	14.53	28.18	22.96	90.53	90.58
Sanderson-Windmeijer excluded Entrant p-value	<0.001	<0.001	<0.001	<0.001	<0.001
Sanderson-Windmeijer excluded Exit F stat.	31.20	51.85	239.8	306.4	221.7
Sanderson-Windmeijer excluded Exit p-value	<0.001	<0.001	<0.001	<0.001	<0.001
Sargan-Hansen Over-identification Stat.	0.0886	0.318	0.0861	0.150	0.0935
Sargan-Hansen Over-identification p-value	0.766	0.573	0.769	0.698	0.760
Kleibergen-Paap Weak Identification Stat.	9.144	17.93	15.31	54.64	50.98
Sanderson-Windmeijer Weak Inst. Inference Stat.	2.717	5.582	5.058	4.795	0.885
Sanderson-Windmeijer Weak Inst. Inference p-value	0.437	0.134	0.168	0.187	0.829
Anderson-Rubin Weak Inst. Inference Stat.	2.655	5.220	4.121	4.363	0.829
Anderson-Rubin Weak Inst. Inference p-value	0.448	0.156	0.249	0.225	0.842
Kleibergen-Paap Under-identification Stat.	22.60	37.04	52.07	91.85	106.6
Kleibergen-Paap Under-identification p-value	<0.001	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses, clustered at the ED level. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant.
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Instrumental Variables estimates, Metropolitan Emergency Departments.

	m=2	m=4	m=6	m=8	m=10
Entrant (δ_1)	206.9	-15,786**	-2,325	-365.1	-3,438
	(11,685)	(7,179)	(5,116)	(4,714)	(3,052)
Exit (δ_2)	-1,897	4,608**	1,446	-191.4	414.4
	(2,870)	(2,229)	(1,069)	(954.6)	(428.9)
Lag N (δ_3)	-840.3	-5,194***	-1,501*	-540.8	-761.5**
	(3,293)	(1,754)	(895.6)	(784.2)	(361.9)
All population ('000)	-2.418	10.40	3.371	1.115	3.896
	(7.859)	(7.160)	(7.685)	(8.068)	(6.882)
Population in poverty ('000)	2.007	-9.590	-2.399	-1.018	-6.772
	(5.211)	(6.004)	(6.985)	(8.303)	(7.282)
Median household income ('000)	-105.9**	-126.3***	-120.4***	-117.2***	-128.7***
	(44.57)	(44.37)	(44.25)	(44.47)	(44.35)
Number of PCPs ('0)	-21.03**	-25.43***	-21.22**	-20.04**	-18.66**
	(9.357)	(9.725)	(9.271)	(9.303)	(9.272)
Number of PAs ('0)	42.38	-6.433	21.77	28.82	13.94
	(31.94)	(23.50)	(31.26)	(28.42)	(27.12)
Population not insured ('000)	13.44**	8.459	11.45**	12.08**	11.35**
	(5.435)	(5.453)	(5.411)	(5.224)	(5.051)
Time fixed effects	Y	Y	Y	Y	Y

	m=2	m=4	m=6	m=8	m=10
Observations	15,995	15,995	15,995	15,995	15,995
R-squared	0.128	0.066	0.128	0.130	0.108
Number of EDs	2,832	2,832	2,832	2,832	2,832
Sanderson-Windmeijer excluded Entrant F stat.	14.23	19.83	27.42	14.20	22.51
Sanderson-Windmeijer excluded Entrant p-value	<0.001	<0.001	<0.001	<0.001	<0.001
Sanderson-Windmeijer excluded Exit F stat.	30.74	74.72	50.41	92.29	239.4
Sanderson-Windmeijer excluded Exit p-value	<0.001	<0.001	<0.001	<0.001	<0.001
Sargan-Hansen Over-identification Stat.	1.325	1.037	1.398	1.365	1.310
Sargan-Hansen Over-identification p-value	0.250	0.308	0.237	0.243	0.252
Kleibergen-Paap Weak Identification Stat.	9.032	12.99	17.44	9.462	15.02
Sanderson-Windmeijer Weak Inst. Inference Stat.	3.406	8.873	4.413	1.856	3.008
Sanderson-Windmeijer Weak Inst. Inference p-value	0.333	0.0310	0.220	0.603	0.390
Anderson-Rubin Weak Inst. Inference Stat.	3.142	7.380	4.181	1.697	2.623
Anderson-Rubin Weak Inst. Inference p-value	0.370	0.0607	0.243	0.638	0.453
Kleibergen-Paap Under-identification Stat.	22.59	31.42	36.61	25.91	51.09
Kleibergen-Paap Under-identification p-value	<0.001	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses, clustered at the ED level. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant.
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Poisson regressions of mortality rates, Heart-related conditions – aggregation from Ordinary Least Squares results.

	m=2	m=6	m=10	m=14	m=18
Visits gained (ϕ_1) (‘000)	1.0004***	0.9999	1.0000	1.0001	1.0001**
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Visits lost (ϕ_2) (‘000)	0.9996	1.0006***	1.0004***	1.0003***	1.0003***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Unreliable rate	0.7705***	0.7729***	0.7717***	0.7718***	0.7719***
	(0.0136)	(0.0131)	(0.0131)	(0.0131)	(0.0131)
All visits (‘000)	1.0000	1.0000	1.0000	1.0000	1.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population in poverty (‘000)	0.9998**	0.9996***	0.9997***	0.9997***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Median household income (‘000)	0.9943***	0.9938***	0.9943***	0.9944***	0.9943***
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Number of PCPs (‘0)	0.9999	1.0001	0.9999	1.0000	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of PAs (‘0)	0.9988***	0.9989**	0.9990*	0.9990**	0.9990**
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Population not insured (‘000)	0.9998***	0.9999***	0.9999***	0.9999***	0.9999***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log all population (‘000,000)	1	1	1	1	1

	m=2	m=6	m=10	m=14	m=18
	.	.	.	.	.
Constant	425.69***	432.14***	424.31***	424.05***	424.18***
	(14.78)	(13.82)	(12.91)	(13.08)	(13.19)
α	0.0857***	0.0843***	0.0856***	0.0856***	0.0856***
	(0.0192)	(0.0173)	(0.0178)	(0.0178)	(0.0177)
Mean mortality rate	300.36	300.36	300.36	300.36	300.36
Aggregation estimates	Basic	Basic	Basic	Basic	Basic
Time fixed effects	Y	Y	Y	Y	Y
Observations	17,646	17,646	17,646	17,646	17,646
Number of counties	3,021	3,021	3,021	3,021	3,021

Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant. Heart-related: ischemic heart disease (ICD 10-CM I20-I25), pulmonary heart disease (ICD-10 I26-I28), other forms of heart disease (ICD-10 I30-I51), and cerebrovascular disease (ICD 10-CM I60-I69).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9. Poisson regressions of mortality rates, Heart-related conditions – aggregation from Instrumental Variables results.

	m=2	m=6	m=10	m=14	m=18
Visits gained (ϕ_1) ('000)	1.0003**	1.0001	1.0000	1.0000	1.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9998	1.0003***	1.0001**	1.0001**	1.0002***
	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Unreliable rate	0.7712***	0.7718***	0.7722***	0.7720***	0.7721***
	(0.0134)	(0.0132)	(0.0130)	(0.0131)	(0.0130)
All volume ('000)	1.0000	1.0000	1.0000	1.0000	1.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population in poverty ('000)	0.9998**	0.9997***	0.9997***	0.9998***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Median household income ('000)	0.9942***	0.9943***	0.9943***	0.9944***	0.9943***
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Number of PCPs ('0)	0.9999	1.0000	1.0000	1.0000	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of PAs ('0)	0.9987***	0.9993	0.9991*	0.9990*	0.9989**
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Population not insured ('000)	0.9999**	0.9998***	0.9999***	0.9999***	0.9999***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Log all population ('000,000)	1	1	1	1	1
	.	.	.	.	.

	m=2	m=6	m=10	m=14	m=18
Constant	427.22***	426.05***	423.40***	422.70***	423.52***
	(14.90)	(13.15)	(12.60)	(12.81)	(12.92)
α	0.0852***	0.0853***	0.0857***	0.0858***	0.0856***
	(0.0184)	(0.0178)	(0.0175)	(0.0176)	(0.0176)
Mean mortality rate	300.36	300.36	300.36	300.36	300.36
Aggregation estimates	IV	IV	IV	IV	IV
Time fixed effects	Y	Y	Y	Y	Y
Observations	17,646	17,646	17,646	17,646	17,646
Number of counties	3,021	3,021	3,021	3,021	3,021

Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant. Heart-related: ischemic heart disease (ICD 10-CM I20-I25), pulmonary heart disease (ICD-10 I26-I28), other forms of heart disease (ICD-10 I30-I51), and cerebrovascular disease (ICD 10-CM I60-I69).
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Poisson regressions of mortality rates, Accident-related deaths – aggregation from Ordinary Least Squares results.

	m=2	m=6	m=10	m=14	m=18
Visits gained (ϕ_1)	0.9999	0.9998	1.0001	1.0001	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
Visits lost (ϕ_2)	0.9995	1.0000	1.0001	1.0000	1.0000
	(0.0009)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Unreliable rate	0.7715***	0.7720***	0.7716***	0.7718***	0.7718***
	(0.0194)	(0.0189)	(0.0197)	(0.0194)	(0.0193)
All visits (‘000)	1.0000	1.0001	1.0000	1.0000	1.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Population in poverty (‘000)	0.9994**	0.9993***	0.9992***	0.9993***	0.9993***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Median household income (‘000)	0.9892***	0.9889***	0.9890***	0.9890***	0.9890***
	(0.0019)	(0.0017)	(0.0018)	(0.0018)	(0.0018)
Number of PCPs (‘0)	1.0002	1.0003	1.0003	1.0002	1.0002
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Number of PAs (‘0)	1.0005	1.0002	1.0000	1.0001	1.0001
	(0.0009)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Population not insured (‘000)	0.9997**	0.9997***	0.9997***	0.9997***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log all population (‘000,000)	1	1	1	1	1
	.	.	.	.	.

	m=2	m=6	m=10	m=14	m=18
Constant	98.83***	99.92***	99.69***	99.74***	99.80***
	(5.51)	(5.12)	(5.32)	(5.26)	(5.23)
α	0.1060***	0.1050***	0.1053***	0.1052***	0.1052***
	(0.0327)	(0.0314)	(0.0330)	(0.0323)	(0.0321)
Mean mortality rate	55.26	55.26	55.26	55.26	55.26
Aggregation estimates	Basic	Basic	Basic	Basic	Basic
Time fixed effects	Y	Y	Y	Y	Y
Observations	11,901	11,901	11,901	11,901	11,901
Number of counties	2,411	2,411	2,411	2,411	2,411

Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant. Accident related: transport accidents (ICD-10-CM V01-V99) and other external causes of injuries (ICD-10-CM W00-X59).
*** p<0.01, ** p<0.05, * p<0.1

Table 11. Poisson regressions of mortality rates, Accident-related deaths – aggregation from Instrumental Variables results.

	m=2	m=6	m=10	m=14	m=18
Visits gained (ϕ_1)	0.9999	1.0000	1.0000	1.0000	1.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2)	0.9996	1.0001	1.0000*	1.0000	1.0000
	(0.0008)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Unreliable rate	0.7716***	0.7715***	0.7715***	0.7715***	0.7715***
	(0.0191)	(0.0197)	(0.0197)	(0.0198)	(0.0198)
All visits (‘000)	1.0001	1.0000	1.0000	1.0000	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Population in poverty (‘000)	0.9994**	0.9993***	0.9993***	0.9993***	0.9993***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Median household income (‘000)	0.9892***	0.9890***	0.9891***	0.9891***	0.9890***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Number of PCPs (‘0)	1.0002	1.0003	1.0003	1.0003	1.0003
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Number of PAs (‘0)	1.0005	1.0001	1.0001	1.0000	1.0000
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Population not insured (‘000)	0.9997***	0.9997***	0.9997***	0.9997***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log all population (‘000,000)	1	1	1	1	1
	.	.	.	.	.

	m=2	m=6	m=10	m=14	m=18
Constant	98.90***	99.64***	99.46***	99.51***	99.68***
	(5.42)	(5.29)	(5.30)	(5.34)	(5.33)
α	0.1060***	0.1052***	0.1053***	0.1053***	0.1052***
	(0.0323)	(0.0328)	(0.0330)	(0.0332)	(0.0332)
Mean mortality rate	55.26	55.26	55.26	55.26	55.26
Aggregation estimates	IV	IV	IV	IV	IV
Time fixed effects	Y	Y	Y	Y	Y
Observations	11,901	11,901	11,901	11,901	11,901
Number of counties	2,411	2,411	2,411	2,411	2,411

Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant. Accident related: transport accidents (ICD-10-CM V01-V99) and other external causes of injuries (ICD-10-CM W00-X59).

*** p<0.01, ** p<0.05, * p<0.1

Table 12. Poisson regressions of mortality rates, Respiratory-related conditions – aggregation from Ordinary Least Squares results.

	m=2	m=6	m=10	m=14	m=18
Visits gained (ϕ_1) (‘000)	1.0004*	1.0000	0.9998	0.9999**	0.9999***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
Visits lost (ϕ_2) (‘000)	1.0001	1.0003	1.0000	1.0000	1.0000
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Unreliable rate	0.7522***	0.7529***	0.7528***	0.7526***	0.7525***
	(0.0161)	(0.0153)	(0.0155)	(0.0157)	(0.0159)
All visits (‘000)	0.9999	0.9999	1.0000	1.0000	1.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population in poverty (‘000)	0.9996***	0.9996***	0.9997***	0.9997***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Median household income (‘000)	0.9856***	0.9855***	0.9857***	0.9856***	0.9857***
	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0013)
Number of PCPs (‘0)	1.0000	1.0001	1.0000	1.0000	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of PAs (‘0)	0.9990**	0.9994	0.9995	0.9994	0.9993
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Population not insured (‘000)	0.9998***	0.9997***	0.9997***	0.9997***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log all population (‘000,000)	1	1	1	1	1
	.	.	.	.	.

	m=2	m=6	m=10	m=14	m=18
Constant	133.44***	133.41***	132.77***	132.83***	132.74***
	(4.82)	(4.63)	(4.73)	(4.74)	(4.78)
α	0.1119***	0.1118***	0.1121***	0.1122***	0.1123***
	(0.0358)	(0.0337)	(0.0340)	(0.0346)	(0.0350)
Mean mortality rate	65.70	65.70	65.70	65.70	65.70
Aggregation estimates	Basic	Basic	Basic	Basic	Basic
Time fixed effects	Y	Y	Y	Y	Y
Observations	12,518	12,518	12,518	12,518	12,518
Number of counties	2,470	2,470	2,470	2,470	2,470

Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant. Respiratory-related: chronic lower respiratory disease (ICD 10-CM J40-J47).
*** p<0.01, ** p<0.05, * p<0.1

Table 13. Poisson regressions of mortality rates, Respiratory-related conditions – aggregation from Instrumental Variables results.

	m=2	m=6	m=10	m=14	m=18
Visits gained (ϕ_1) (‘000)	1.0003**	1.0000	1.0000	1.0000*	0.9999***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) (‘000)	1.0002	1.0000	1.0000	1.0000	1.0000
	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Unreliable rate	0.7524***	0.7528***	0.7526***	0.7524***	0.7520***
	(0.0158)	(0.0155)	(0.0155)	(0.0156)	(0.0161)
All visits (‘000)	0.9999	0.9999	0.9999	0.9999	0.9999
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population in poverty (‘000)	0.9996***	0.9997***	0.9997***	0.9997***	0.9998***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Median household income (‘000)	0.9855***	0.9857***	0.9857***	0.9857***	0.9857***
	(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Number of PCPs (‘0)	1.0000	1.0000	1.0000	1.0000	1.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of PAs (‘0)	0.9991*	0.9994	0.9993	0.9993	0.9991*
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Population not insured (‘000)	0.9998***	0.9997***	0.9997***	0.9997***	0.9997***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log all population (‘000,000)	1	1	1	1	1
	.	.	.	.	.

	m=2	m=6	m=10	m=14	m=18
Constant	133.54***	132.86***	132.77***	132.80***	132.68***
	(4.75)	(4.73)	(4.76)	(4.80)	(4.91)
α	0.1117***	0.1121***	0.1121***	0.1121***	0.1123***
	(0.0350)	(0.0340)	(0.0342)	(0.0345)	(0.0357)
Mean mortality rate	65.70	65.70	65.70	65.70	65.70
Aggregation estimates	IV	IV	IV	IV	IV
Time fixed effects	Y	Y	Y	Y	Y
Observations	12,518	12,518	12,518	12,518	12,518
Number of counties	2,470	2,470	2,470	2,470	2,470

Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. ED: Emergency Department. PCP: Primary Care physicians. PA: Physician Assistant. Respiratory-related: chronic lower respiratory disease (ICD 10-CM J40-J47).
*** p<0.01, ** p<0.05, * p<0.1

Table 14 Disparities in mortality rates, Heart-related deaths – aggregation from Ordinary Least Squares results.

	m=2	m=6	m=10	m=14	m=18
Male (N=16,291)					
Visits gained (ϕ_1) (‘000)	1.0004***	0.9999	1.0000	1.0001	1.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Visits lost (ϕ_2) (‘000)	0.9998	1.0007***	1.0004***	1.0003***	1.0002***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Female (N=16,180)					
Visits gained (ϕ_1) (‘000)	1.0004**	0.9999	1.0000	1.0001	1.0001*
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Visits lost (ϕ_2) (‘000)	0.9997	1.0006***	1.0004**	1.0003**	1.0002***
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
White (N=17,495)					
Visits gained (ϕ_1) (‘000)	1.0005***	1.0000	1.0001	1.0001*	1.0001**
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Visits lost (ϕ_2) (‘000)	0.9995	1.0007***	1.0005**	1.0004***	1.0003***
	(0.0004)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Non-White (N=5,951)					
Visits gained (ϕ_1) (‘000)	1.0005**	1.0001	1.0002**	1.0000	1.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Visits lost (ϕ_2) (‘000)	0.9996	1.0004**	1.0002**	1.0001**	1.0001**
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)

	m=2	m=6	m=10	m=14	m=18
Aggregation estimates	Basic	Basic	Basic	Basic	Basic
Time fixed effects	Y	Y	Y	Y	Y

Each pair of rows correspond to a Poisson regression. Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. Heart-related: ischemic heart disease (ICD 10-CM I20-I25), pulmonary heart disease (ICD-10 I26-I28), other forms of heart disease (ICD-10 I30-I51), and cerebrovascular disease (ICD 10-CM I60-I69).
*** p<0.01, ** p<0.05, * p<0.1

Table 15. Disparities in mortality rates, Heart-related deaths – aggregation from Instrumental Variables results.

	m=2	m=6	m=10	m=14	m=18
Male (N=16,291)					
Visits gained (ϕ_1) ('000)	1.0003***	1.0001*	1.0000*	1.0000	1.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9999	1.0003***	1.0001**	1.0001**	1.0001***
	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Female (N=16,180)					
Visits gained (ϕ_1) ('000)	1.0003**	1.0001*	1.0000*	1.0000	1.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9998	1.0003**	1.0001**	1.0001**	1.0002**
	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
White (N=17,495)					
Visits gained (ϕ_1) ('000)	1.0004***	1.0001	1.0000	1.0000	1.0001*
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9997	1.0004**	1.0002**	1.0001**	1.0002***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Non-White (N=5,951)					
Visits gained (ϕ_1) ('000)	1.0003*	1.0001***	1.0000***	1.0000**	1.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9998	1.0002***	1.0001***	1.0001**	1.0001**
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)

	m=2		m=6		m=10		m=14		m=18	
Aggregation estimates	IV		IV		IV		IV		IV	
Time fixed effects		Y		Y		Y		Y		Y

Each pair of rows correspond to a Poisson regression. Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. Heart-related: ischemic heart disease (ICD 10-CM I20-I25), pulmonary heart disease (ICD-10 I26-I28), other forms of heart disease (ICD-10 I30-I51), and cerebrovascular disease (ICD 10-CM I60-I69).
*** p<0.01, ** p<0.05, * p<0.1

Table 16. Disparities in mortality rates, Accident-related deaths – aggregation from Ordinary Least Squares results.

	m=2	m=6	m=10	m=14	m=18
Male (N=16,291)					
Visits gained (ϕ_1) (‘000)	1.0000	0.9999	1.0000	1.0000	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
Visits lost (ϕ_2) (‘000)	1.0000	1.0001	1.0000	1.0000	0.9999
	(0.0008)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Female (N=16,180)					
Visits gained (ϕ_1) (‘000)	1.0000	0.9998	1.0002	1.0001	1.0001
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Visits lost (ϕ_2) (‘000)	0.9989	1.0000	1.0002	1.0001	1.0001
	(0.0012)	(0.0004)	(0.0002)	(0.0001)	(0.0001)
White (N=17,495)					
Visits gained (ϕ_1) (‘000)	0.9998	0.9999	1.0002	1.0001**	1.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
Visits lost (ϕ_2) (‘000)	1.0002	1.0000	1.0000	1.0000	1.0000
	(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Non-White (N=5,951)					
Visits gained (ϕ_1) (‘000)	1.0009***	0.9999	0.9994	0.9998	0.9999
	(0.0002)	(0.0005)	(0.0005)	(0.0001)	(0.0001)
Visits lost (ϕ_2) (‘000)	0.9979*	0.9999	1.0001	1.0000	1.0000
	(0.0012)	(0.0005)	(0.0002)	(0.0002)	(0.0001)

	m=2	m=6	m=10	m=14	m=18
Aggregation estimates	Basic	Basic	Basic	Basic	Basic
Time fixed effects	Y	Y	Y	Y	Y

Each pair of rows correspond to a Poisson regression. Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. Accident related: transport accidents (ICD-10-CM V01-V99) and other external causes of injuries (ICD-10-CM W00-X59).
*** p<0.01, ** p<0.05, * p<0.1

Table 17. Disparities in mortality rates, Accident-related deaths – aggregation from Instrumental Variables results.

	m=2	m=6	m=10	m=14	m=18
Male (N=16,291)					
Visits gained (ϕ_1) ('000)	0.9999	1.0000	1.0000	1.0000**	0.9999**
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0000	1.0000	1.0000	1.0000	0.9999*
	(0.0007)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Female (N=16,180)					
Visits gained (ϕ_1) ('000)	0.9999	1.0000	1.0000	1.0000	1.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9991	1.0002*	1.0001**	1.0001**	1.0001
	(0.0011)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
White (N=17,495)					
Visits gained (ϕ_1) ('000)	0.9998*	1.0000	1.0000	1.0000	1.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0002	1.0000	1.0000	1.0000	1.0000
	(0.0005)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Non-White (N=5,951)					
Visits gained (ϕ_1) ('000)	1.0004**	1.0000	1.0000	1.0000	0.9999*
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	0.9983	1.0001	1.0001	1.0001	1.0000
	(0.0012)	(0.0001)	(0.0000)	(0.0000)	(0.0001)

	m=2	m=6	m=10	m=14	m=18
Aggregation estimates	IV	IV	IV	IV	IV
Time fixed effects	Y	Y	Y	Y	Y

Each pair of rows correspond to a Poisson regression. Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. Accident related: transport accidents (ICD-10-CM V01-V99) and other external causes of injuries (ICD-10-CM W00-X59).
*** p<0.01, ** p<0.05, * p<0.1

Table 18. Disparities in mortality rates, Respiratory-related conditions – aggregation from Ordinary Least Squares results.

	m=2	m=6	m=10	m=14	m=18
Male (N=16,291)					
Visits gained (ϕ_1) ('000)	1.0005*	1.0000	0.9998	0.9999**	0.9999**
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0002	1.0003	1.0000	1.0000	1.0000
	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Female (N=16,180)					
Visits gained (ϕ_1) ('000)	1.0004**	1.0000	0.9999	0.9999***	0.9999***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0003	1.0003	1.0000	1.0000	1.0000
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
White (N=17,495)					
Visits gained (ϕ_1) ('000)	1.0005**	1.0000	0.9999	0.9999	0.9999
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0001	1.0004*	1.0001	1.0001	1.0001
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Non-White (N=5,951)					
Visits gained (ϕ_1) ('000)	1.0002	1.0002	0.9994**	0.9997***	0.9998***
	(0.0003)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Visits lost (ϕ_2) ('000)	0.9998	0.9999	0.9998**	0.9998***	0.9998**
	(0.0005)	(0.0003)	(0.0001)	(0.0001)	(0.0001)

	m=2	m=6	m=10	m=14	m=18
Aggregation estimates	Basic	Basic	Basic	Basic	Basic
Time fixed effects	Y	Y	Y	Y	Y

Each pair of rows correspond to a Poisson regression. Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. Respiratory-related: chronic lower respiratory disease (ICD 10-CM J40-J47).
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Disparities in mortality rates, Respiratory-related conditions – aggregation from Instrumental Variables results.

	m=2	m=6	m=10	m=14	m=18
Male (N=16,291)					
Visits gained (ϕ_1) ('000)	1.0004**	0.9999	1.0000**	1.0000**	0.9999**
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0003	1.0000	1.0000	1.0000	1.0000
	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Female (N=16,180)					
Visits gained (ϕ_1) ('000)	1.0003*	1.0000	1.0000	1.0000*	0.9999***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0003	1.0000	1.0000	1.0000	1.0000
	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
White (N=17,495)					
Visits gained (ϕ_1) ('000)	1.0004**	1.0000	1.0000	1.0000*	0.9999**
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0001	1.0001	1.0000	1.0000	1.0000
	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Non-White (N=5,951)					
Visits gained (ϕ_1) ('000)	1.0001	1.0000	1.0000	1.0000**	0.9999***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Visits lost (ϕ_2) ('000)	1.0001	0.9999	0.9999*	0.9999**	0.9999**
	(0.0004)	(0.0002)	(0.0000)	(0.0000)	(0.0001)

	m=2	m=6	m=10	m=14	m=18
Aggregation estimates	IV	IV	IV	IV	IV
Time fixed effects	Y	Y	Y	Y	Y

Each pair of rows correspond to a Poisson regression. Incidence Rate Ratios reported. Standard errors in parentheses. County random effects. Respiratory-related: chronic lower respiratory disease (ICD 10-CM J40-J47).
*** p<0.01, ** p<0.05, * p<0.1

Table 20. Descriptive statistics, hospitals in Acute Inpatient Prospective Payment System and NEDI-USA

	2005	2007	2009	2011	2012	2013
Hospitals in IPPS[1]	3,051	3,093	3,107	3,114	3,086	3,033
Metropolitan	2,033	2,069	2,078	2,085	2,074	2,044
Adjacent to metropolitan	597	601	604	607	597	583
Rural	421	423	425	422	415	406
Academic	110	111	139	139	146	173
Critical Access	7	4	1	0	0	0
Parent to FSED	51	66	91	113	131	145
Parent and FSED in same county	39	48	62	77	89	99
Case mix measures						
Transfer-adjusted Cases	3,564.20	3,412.95	3,261.84	3,235.76	3,127.42	3,079.09
Case Mix Index	1.3707	1.3757	1.44	1.457	1.4757	1.5043
Transfer-Adjusted Case Mix Index	1.3586	1.3632	1.4274	1.4448	1.4638	1.4926
Payer mix measures						
Disproportionate Share percent	26.94%	27.37%	27.84%	29.00%	29.00%	28.98%

Source: Centers for Medicare and Medicaid Services IPPS Final Rules 2007-2015 and NEDI-USA 2005-2013. [1] 81.2 percent of hospitals in IPPS had a match in NEDI-USA data. ED: Emergency Department. FSED: Freestanding Emergency Department. IPPS: Inpatient Prospective Payment System.

Table 21. Freestanding Emergency Departments within 6-mile radius, all hospitals – Ordinary Least Squares results.

	Volume	Case Mix		Payer Mix
	CASETA (1)	CMI (2)	TACMI (3)	DSHPT (4)
Number of FSEDs in area	-44.75	0.0256***	0.0257***	-0.00542**
	(40.82)	(0.00953)	(0.00951)	(0.00226)
	-1.375	*1.763*	*1.787*	*-1.895*
	[-3.83 ; 1.08]	[0.48 ; 3.05]	[0.49 ; 3.08]	[-3.44 ; -0.35]
Number of FSEDs operated	-259.5***	-0.00926*	-0.00919*	0.00444
	(85.32)	(0.00561)	(0.00551)	(0.00312)
	-7.974	*-0.638*	*-0.638*	*1.551*
	[-13.11 ; -2.84]	[-1.40 ; 0.12]	[-1.40 ; 0.11]	[-0.59 ; 3.69]
Population over 65 years old	0.118	0.000304***	0.000314***	0.000218***
	(0.362)	(6.82e-05)	(6.66e-05)	(4.26e-05)
Median household income	14.64***	0.00102**	0.00104**	3.87e-05
	(2.437)	(0.000412)	(0.000408)	(0.000229)
Number of beds	6.477***	8.05e-05*	8.68e-05**	4.30e-05*
	(0.489)	(4.16e-05)	(4.12e-05)	(2.29e-05)
Population in poverty	0.546***	0.000107***	0.000110***	-8.87e-05***
	(0.147)	(3.00e-05)	(2.95e-05)	(1.76e-05)
Constant	1,604***	1.275***	1.259***	0.246***
	(145.5)	(0.0219)	(0.0217)	(0.0119)
Radius (miles)	6	6	6	6
Time fixed effects	Yes	Yes	Yes	Yes

Area	All	All	All	All
Observations	21,367	21,367	21,367	21,367
R-squared	0.255	0.330	0.339	0.102
Number of hospitals	3,174	3,174	3,174	3,174
Fraction of within variance	0.950	0.908	0.909	0.928

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 22. Freestanding Emergency Departments within 6-mile radius, metropolitan hospitals – Ordinary Least Squares results.

	Volume	Case Mix		Payer Mix
	CASETA	CMI	TACMI	DSHPT
	(5)	(6)	(7)	(8)
Number of FSEDs in area	-37.29	0.0238**	0.0239**	-0.00680***
	(40.95)	(0.00949)	(0.00947)	(0.00229)
	-0.923	*1.535*	*1.555*	*-2.354*
	[-2.91 ; 1.06]	[0.34 ; 2.73]	[0.35 ; 2.76]	[-3.91 ; -0.80]
Number of FSEDs operated	-257.3***	-0.0119**	-0.0119**	0.00324
	(88.93)	(0.00589)	(0.00579)	(0.00318)
	-6.369	*-0.767*	*-0.771*	*1.123*
	[-10.68 ; -2.06]	[-1.51 ; -0.02]	[-1.51 ; -0.03]	[-1.04 ; 3.29]
Population over 65 years old	0.561	0.000192***	0.000199***	0.000143***
	(0.392)	(7.04e-05)	(6.86e-05)	(4.46e-05)
Median household income	20.45***	0.00134**	0.00136***	-0.000292
	(3.389)	(0.000522)	(0.000518)	(0.000275)
Number of beds	6.866***	5.57e-05	6.14e-05	3.06e-05
	(0.509)	(4.53e-05)	(4.50e-05)	(2.46e-05)
Population in poverty	0.614***	0.000116***	0.000118***	-8.80e-05***
	(0.156)	(3.08e-05)	(3.01e-05)	(1.78e-05)
Constant	1,548***	1.338***	1.321***	0.268***
	(214.4)	(0.0308)	(0.0306)	(0.0161)
Radius (miles)	6	6	6	6
Time fixed effects	Yes	Yes	Yes	Yes

Area	Metropolitan	Metropolitan	Metropolitan	Metropolitan
Observations	14,316	14,316	14,316	14,316
R-squared	0.243	0.338	0.347	0.150
Number of hospitals	2,137	2,137	2,137	2,137
Fraction of within variance	0.947	0.892	0.894	0.949

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 23. Freestanding Emergency Departments within 2 to 10-mile radius, All hospitals – Ordinary Least Squares results.

		Volume	Case Mix		Payer Mix
		CASETA (1)	CMI (2)	TACMI (3)	DSHPT (4)
Radius = 2 miles	Number of FSEDs in area	-129.9	0.00197	0.00146	-0.00456
		(109.3)	(0.0220)	(0.0218)	(0.00542)
		-3.991	*0.135*	*0.101*	*-1.594*
		[-10.57 ; 2.59]	[-2.83 ; 3.10]	[-2.87 ; 3.07]	[-5.31 ; 2.12]
	Number of FSEDs operated	-259.1***	-0.00909	-0.00902	0.00442
		(85.41)	(0.00561)	(0.00551)	(0.00312)
		-7.962	*-0.626*	*-0.626*	*1.547*
		[-13.11 ; -2.82]	[-1.38 ; 0.13]	[-1.38 ; 0.12]	[-0.59 ; 3.69]
Radius = 4 miles	Number of FSEDs in area	-91.89	0.0302*	0.0307**	-0.00646**
		(60.68)	(0.0155)	(0.0155)	(0.00329)
		-2.824	2.083	2.131	-2.259
		[-6.48 ; 0.83]	[-0.01 ; 4.18]	[0.02 ; 4.24]	[-4.51 ; -0.00]
	Number of FSEDs operated	-259.0***	-0.00935*	-0.00929*	0.00446
		(85.36)	(0.00561)	(0.00552)	(0.00312)
		-7.959	-0.644	-0.645	1.558
		[-13.10 ; -2.82]	[-1.40 ; 0.11]	[-1.4 ; 0.11]	[-0.58 ; 3.70]
Radius = 8 miles	Number of FSEDs in area	-20.46	0.0227***	0.0230***	-0.00524***
		(27.87)	(0.00649)	(0.00626)	(0.00173)
		-0.629	1.562	1.598	-1.833
		[-2.31 ; 1.05]	[0.69 ; 2.44]	[0.75 ; 2.45]	[-3.02 ; -0.65]
	Number of FSEDs operated	-259.3***	-0.00967*	-0.00961*	0.00453

		(85.38)	(0.00556)	(0.00547)	(0.00312)
		-7.967	-0.666	-0.668	1.586
		[-13.11 ; -2.82]	[-1.42 ; 0.08]	[-1.41 ; 0.08]	[-0.56 ; 3.73]
Radius = 10 miles	Number of FSEDs in area	-27.60	0.0156***	0.0158***	-0.00429***
		(22.86)	(0.00459)	(0.00446)	(0.00147)
		-0.848	*1.075*	*1.101*	*-1.502*
		[-2.23 ; 0.53]	[0.46 ; 1.70]	[0.50 ; 1.71]	[-2.51 ; -0.50]
	Number of FSEDs operated	-258.1***	-0.0100*	-0.00998*	0.00466
		(85.48)	(0.00559)	(0.00549)	(0.00313)
		-7.932	*-0.691*	*-0.693*	*1.630*
		[-13.08 ; -2.78]	[-1.45 ; 0.06]	[-1.44 ; 0.05]	[-0.52 ; 3.78]
Area		All	All	All	All

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 24. Freestanding Emergency Departments within 2 to 10-mile radius, Metropolitan hospitals – Ordinary Least Squares results.

		Volume	Case Mix		Payer Mix
		CASETA (5)	CMI (6)	TACMI (7)	DSHPT (8)
Radius = 2 miles	Number of FSEDs in area	-117.4	-0.000540	-0.00110	-0.00563
		(109.0)	(0.0220)	(0.0218)	(0.00539)
		-2.905	-0.0348	*-0.0713*	*-1.951*
		[-8.19 ; 2.38]	[-2.81 ; 2.74]	[-2.85 ; 2.71]	[-5.61 ; 1.71]
	Number of FSEDs operated	-256.9***	-0.0118**	-0.0117**	0.00324
		(89.03)	(0.00589)	(0.00579)	(0.00319)
		-6.357	-0.760	*-0.764*	*1.124*
		[-10.68 ; -2.04]	[-1.50 ; -0.02]	[-1.50 ; -0.03]	[-1.04 ; 3.29]
Radius = 4 miles	Number of FSEDs in area	-84.89	0.0288*	0.0292*	-0.00798**
		(61.11)	(0.0155)	(0.0155)	(0.00335)
		-2.101	1.855	1.899	-2.765
		[-5.07 ; 0.86]	[-0.11 ; 3.82]	[-0.08 ; 3.88]	[-5.04 ; -0.49]
	Number of FSEDs operated	-256.8***	-0.0120**	-0.0120**	0.00328
		(88.97)	(0.00589)	(0.00579)	(0.00319)
		-6.357	-0.775	-0.779	1.135
		[-10.67 ; -2.04]	[-1.52 ; -0.03]	[-1.52 ; -0.04]	[-1.03 ; 3.30]
Radius = 8 miles	Number of FSEDs in area	-14.17	0.0211***	0.0214***	-0.00641***
		(28.09)	(0.00650)	(0.00626)	(0.00176)
		-0.351	1.362	1.393	-2.220
		[-1.71 ; 1.01]	[0.54 ; 2.18]	[0.60 ; 2.19]	[-3.42 ; -1.02]
	Number of FSEDs operated	-257.2***	-0.0123**	-0.0122**	0.00336

		(88.99)	(0.00585)	(0.00574)	(0.00320)
		-6.365	-0.791	-0.796	1.163
		[-10.68 ; -2.05]	[-1.53 ; -0.05]	[-1.54 ; -0.06]	[-1.01 ; 3.33]
Radius = 10 miles	Number of FSEDs in area	-21.28	0.0145***	0.0147***	-0.00520***
		(23.04)	(0.00460)	(0.00446)	(0.00149)
		-0.527	*0.935*	*0.958*	*-1.803*
		[-1.64 ; 0.59]	[0.35 ; 1.52]	[0.39 ; 1.53]	[-2.82 ; -0.79]
	Number of FSEDs operated	-256.3***	-0.0126**	-0.0126**	0.00351
		(89.08)	(0.00588)	(0.00577)	(0.00321)
		-6.343	*-0.815*	*-0.820*	*1.217*
		[-10.66 ; -2.02]	[-1.56 ; -0.07]	[-1.56 ; -0.08]	[-0.96 ; 3.40]
	Area	Metropolitan	Metropolitan	Metropolitan	Metropolitan

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 25. Freestanding Emergency Departments within 6-mile radius, All Hospitals – Instrumental Variables results.

	Volume	Case Mix		Payer Mix
	CASETA	CMI	TACMI	DSHPT
	(1)	(2)	(3)	(4)
Number of FSEDs in area	-998.8*	-0.136	-0.130	-0.0652
	(545.1)	(0.114)	(0.112)	(0.0408)
	-30.70	*-9.342*	*-9.013*	*-22.80*
	[-63.53 ; 2.14]	[-24.67 ; 6.00]	[-24.29 ; 6.27]	[-50.76 ; 5.16]
Number of FSEDs operated	321.4	0.348***	0.347***	0.0245
	(369.0)	(0.102)	(0.101)	(0.0263)
	9.879	*23.94*	*24.13*	*8.579*
	[-12.35 ; 32.11]	[10.20 ; 37.68]	[10.40 ; 37.86]	[-9.46 ; 26.62]
Population over 65 years old	0.243	0.000220***	0.000230***	0.000234***
	(0.393)	(8.32e-05)	(8.09e-05)	(4.56e-05)
Median household income	15.67***	0.00110**	0.00112**	0.000176
	(2.620)	(0.000540)	(0.000535)	(0.000239)
Number of beds	6.310***	-5.34e-05	-4.72e-05	3.80e-05
	(0.520)	(6.97e-05)	(6.92e-05)	(2.44e-05)
Population in poverty	0.413**	9.79e-05**	0.000102***	-9.97e-05***
	(0.171)	(3.95e-05)	(3.87e-05)	(1.88e-05)
Radius (miles)	6	6	6	6
Time fixed effects	Yes	Yes	Yes	Yes
Area	All	All	All	All
Observations	21,353	21,353	21,353	21,353

R-squared	0.188	0.049	0.057	0.075
Number of hospitals	3,160	3,160	3,160	3,160
Sanderson-Windmeijer excluded Number F Stat.	19.23	19.23	19.23	19.23
Sanderson-Windmeijer excluded Number p-value	<0.001	<0.001	<0.001	<0.001
Sanderson-Windmeijer excluded Operated F Stat.	18.06	18.06	18.06	18.06
Sanderson-Windmeijer excluded Operated p-value	<0.001	<0.001	<0.001	<0.001
Hansen J Over id Stat	0.122	1.987	1.735	17.73
Hansen J Over id p-value	0.727	0.159	0.188	<0.001
Kleibergen-Paap weak IV Stat.	12.19	12.19	12.19	12.19
Kleibergen-Paap Under id Stat.	34.47	34.47	34.47	34.47
Kleibergen-Paap Under id p-value	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 26. Freestanding Emergency Departments within 6-mile radius, Metropolitan Hospitals – Instrumental Variables results.

	Volume	Case Mix		Payer Mix
	CASETA (1)	CMI (2)	TACMI (3)	DSHPT (4)
Number of FSEDs in area	-823.1	-0.152	-0.152	-0.0718*
	(538.6)	(0.110)	(0.109)	(0.0379)
	-20.37	*-9.772*	*-9.891*	*-24.86*
	[-46.50 ; 5.76]	[-23.61 ; 4.07]	[-23.76 ; 4.00]	[-50.59 ; 0.87]
Number of FSEDs operated	329.1	0.338***	0.340***	0.0178
	(373.5)	(0.101)	(0.101)	(0.0254)
	8.146	*21.78*	*22.13*	*6.158*
	[-9.98 ; 26.27]	[9.00 ; 34.57]	[9.30 ; 34.97]	[-11.08 ; 23.40]
Population over 65 years old	0.629	0.000165*	0.000174**	0.000159***
	(0.416)	(8.64e-05)	(8.45e-05)	(4.70e-05)
Median household income	21.70***	0.00154**	0.00156**	-0.000151
	(3.583)	(0.000700)	(0.000696)	(0.000291)
Number of beds	6.679***	-7.52e-05	-7.03e-05	2.61e-05
	(0.544)	(7.46e-05)	(7.43e-05)	(2.63e-05)
Population in poverty	0.549***	0.000116***	0.000118***	-9.94e-05***
	(0.169)	(3.79e-05)	(3.72e-05)	(1.85e-05)
Radius (miles)	6	6	6	6
Time fixed effects	Yes	Yes	Yes	Yes
Area	Metropolitan	Metropolitan	Metropolitan	Metropolitan
Observations	14,303	14,303	14,303	14,303

R-squared	0.185	-0.006	-0.006	0.104
Number of hospitals	2,124	2,124	2,124	2,124
Sanderson-Windmeijer excluded Number F Stat.	18.55	18.55	18.55	18.55
Sanderson-Windmeijer excluded Number p-value	<0.001	<0.001	<0.001	<0.001
Sanderson-Windmeijer excluded Operated F Stat.	17.43	17.43	17.43	17.43
Sanderson-Windmeijer excluded Operated p-value	<0.001	<0.001	<0.001	<0.001
Hansen J Over id Stat	0.00108	1.588	1.242	17.37
Hansen J Over id p-value	0.974	0.208	0.265	<0.001
Kleibergen-Paap weak IV Stat.	11.71	11.71	11.71	11.71
Kleibergen-Paap Under id Stat.	33.71	33.71	33.71	33.71
Kleibergen-Paap Under id p-value	<0.001	<0.001	<0.001	<0.001

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 27. Freestanding Emergency Departments within 2 to 10-mile radius, All Hospitals – Instrumental Variables results.

		Volume	Case Mix		Payer Mix
		CASETA	CMI	TACMI	DSHPT
		(1)	(2)	(3)	(4)
Radius = 2 miles	Number of FSEDs in area	3,145	-1.622	-1.582	-0.226
		(5,135)	(1.250)	(1.225)	(0.371)
		96.65	*-111.8*	*-109.9*	*-79.19*
		[-212.6 ; 406]	[-280.5 ; 57.0]	[-276.7 ; 56.9]	[-333.2 ; 175]
	Number of FSEDs operated	116.9	0.306***	0.307***	0.00786
		(284.3)	(0.0911)	(0.0898)	(0.0210)
		3.592	*21.10*	*21.35*	*2.750*
		[-13.54 ; 20.72]	[8.8 ; 33.40]	[9.12 ; 33.58]	[-11.6 ; 17.14]
	Kleibergen-Paap weak IV Stat.	3.050	3.050	3.050	3.050
	Hansen J Over id Stat	2.877	2.514	2.269	12.23
Radius = 4 miles	Number of FSEDs in area	-130.9	-0.349	-0.333	-0.134
		(1,074)	(0.271)	(0.267)	(0.0860)
		-4.022	*-24.07*	*-23.15*	*-46.87*
		[-68.7 ; 60.66]	[-60.7 ; 12.5]	[-59.6 ; 13.3]	[-105.8 ; 12.1]
	Number of FSEDs operated	68.74	0.349***	0.348***	0.0221
		(307.1)	(0.0943)	(0.0935)	(0.0244)
		2.113	*24.02*	*24.17*	*7.724*
		[-16.4 ; 20.6]	[11.3 ; 36.8]	[11.4 ; 36.9]	[-9.0 ; 24.4]
	Kleibergen-Paap weak IV Stat.	5.719	5.719	5.719	5.719
	Hansen J Over id Stat	1.610	1.337	1.160	13.15
Ra	Number of FSEDs in area	-823.5**	-0.130*	-0.126*	-0.0749***

		(336.1)	(0.0680)	(0.0673)	(0.0239)
		-25.31	*-8.959*	*-8.754*	*-26.19*
		[-45.5 ; -5.1]	[-18.1 ; 0.2]	[-17.9 ; 0.4]	[-42.6 ; -9.8]
	Number of FSEDs operated	458.0	0.373***	0.372***	0.0471*
		(401.2)	(0.108)	(0.107)	(0.0277)
		14.08	*25.71*	*25.86*	*16.48*
		[-10.1 ; 38.2]	[11.2 ; 40.2]	[11.3 ; 40.4]	[-2.5 ; 35.5]
	Kleibergen-Paap weak IV Stat.	15.61	15.61	15.61	15.61
	Hansen J Over id Stat	0.00337	2.973	2.687	21.84
Radius = 10 miles	Number of FSEDs in area	-720.9***	-0.0886*	-0.0862*	-0.0629***
		(262.0)	(0.0493)	(0.0487)	(0.0186)
		-22.15	*-6.102*	*-5.988*	*-21.99*
		[-37.9 ; -6.4]	[-12.8 ; 0.6]	[-12.6 ; 0.6]	[-34.7 ; -9.2]
	Number of FSEDs operated	604.9	0.386***	0.384***	0.0610**
		(437.9)	(0.109)	(0.108)	(0.0299)
		18.59	*26.56*	*26.70*	*21.33*
		[-7.8 ; 45.0]	[11.8 ; 41.3]	[12.0 ; 41.5]	[0.8 ; 41.9]
	Kleibergen-Paap weak IV Stat.	16.03	16.03	16.03	16.03
	Hansen J Over id Stat	0.00435	2.250	2.026	21.98
	Area	All	All	All	All

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 28. Freestanding Emergency Departments within 2 to 10-mile radius, Metropolitan Hospitals – Instrumental Variables results.

		Volume	Case Mix		Payer Mix
		CASETA (5)	CMI (6)	TACMI (7)	DSHPT (8)
Radius = 2 miles	Number of FSEDs in area	2,759	-1.708	-1.714	-0.258
		(5,009)	(1.216)	(1.200)	(0.357)
		68.28	-110.1	*-111.5*	*-89.51*
		[-174.7 ; 311]	[-263.8 ; 43.6]	[-264.4 ; 41.5]	[-332 ; 152.7]
	Number of FSEDs operated	169.6	0.289***	0.291***	0.00166
		(287.6)	(0.0910)	(0.0901)	(0.0217)
		4.197	18.64	*18.92*	*0.576*
		[-9.75 ; 18.15]	[7.15 ; 30.14]	[7.43 ; 30.40]	[-14.13 ; 15.3]
	Kleibergen-Paap weak IV Stat.	2.850	2.850	2.850	2.850
	Hansen J Over id Stat	1.211	1.754	1.401	9.368
Radius = 4 miles	Number of FSEDs in area	-80.45	-0.364	-0.360	-0.150*
		(1,081)	(0.264)	(0.262)	(0.0837)
		-1.991	*-23.49*	*-23.39*	*-52.05*
		[-54.4 ; 50.4]	[-56.9 ; 9.9]	[-56.8 ; 10]	[-108.9 ; 4.8]
	Number of FSEDs operated	128.3	0.334***	0.335***	0.0152
		(317.4)	(0.0941)	(0.0935)	(0.0244)
		3.175	*21.54*	*21.79*	*5.258*
		[-12.2 ; 18.6]	[9.6 ; 33.4]	[9.9 ; 33.7]	[-11.3 ; 21.8]
	Kleibergen-Paap weak IV Stat.	5.707	5.707	5.707	5.707
	Hansen J Over id Stat	0.594	0.857	0.613	11.31
Ra	Number of FSEDs in area	-682.2**	-0.144**	-0.144**	-0.0799***

		(332.7)	(0.0666)	(0.0661)	(0.0226)
		-16.89	*-9.306*	*-9.347*	*-27.68*
		[-33.0 ; -0.7]	[-17.7 ; -0.9]	[-17.8 ; -0.9]	[-43.0 ; -12.4]
	Number of FSEDs operated	445.2	0.366***	0.367***	0.0412
		(403.0)	(0.107)	(0.107)	(0.0270)
		11.02	*23.57*	*23.90*	*14.29*
		[-8.5 ; 30.6]	[10.0 ; 37.1]	[10.3 ; 37.5]	[-4.1 ; 32.7]
	Kleibergen-Paap weak IV Stat.	15.13	15.13	15.13	15.13
	Hansen J Over id Stat	0.0706	2.722	2.275	22.34
Radius = 10 miles	Number of FSEDs in area	-590.2**	-0.102**	-0.102**	-0.0668***
		(257.3)	(0.0483)	(0.0480)	(0.0176)
		-14.61	*-6.594*	*-6.655*	*-23.16*
		[-27.1 ; -2.1]	[-12.7 ; -0.5]	[-12.8 ; -0.5]	[-35.1 ; -11.2]
	Number of FSEDs operated	567.3	0.383***	0.385***	0.0573*
		(436.9)	(0.109)	(0.109)	(0.0293)
		14.04	*24.69*	*25.01*	*19.85*
		[-7.2 ; 35.2]	[10.9 ; 38.5]	[11.1 ; 38.9]	[-0.05 ; 39.8]
	Kleibergen-Paap weak IV Stat.	15.65	15.65	15.65	15.65
	Hansen J Over id Stat	0.125	2.022	1.663	22.27
	Area	Metropolitan	Metropolitan	Metropolitan	Metropolitan

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent.

*** p<0.01, ** p<0.05, * p<0.1

Table 29. Payer Mix ad hoc analysis, Number of Freestanding Emergency Departments in area – Instrumental Variables results.

	Radius (miles)	2	4	6	8	10
All Areas	Number of FSEDs in area	2.800*	1.070*	0.375***	0.254***	0.224***
		(1.654)	(0.583)	(0.145)	(0.0938)	(0.0841)
		979.3	*374.2*	*131.2*	*88.98*	*78.23*
		[-154.6 ; 2113]	[-25.46 ; 774]	[31.74 ; 230.7]	[24.64 ; 153.3]	[20.58 ; 135.9]
	Sanderson-Windmeijer Weak id. F Stat.	4.079	5.298	21.39	29.74	26.43
	Sanderson-Windmeijer Weak id. p-value	0.0435	0.0214	<0.001	<0.001	<0.001
	Kleibergen-Paap weak IV Stat.	4.079	5.298	21.39	29.74	26.43
	Kleibergen-Paap Under id Stat.	4.099	5.307	21.84	30.29	26.91
	Kleibergen-Paap Under id p-value	0.0429	0.0212	<0.001	<0.001	<0.001
Metropolitan Areas	Number of FSEDs in area	1.933	0.680*	0.247**	0.170**	0.149**
		(1.243)	(0.382)	(0.105)	(0.0695)	(0.0618)
		669.7	*235.5*	*85.41*	*58.82*	*51.67*
		[-174.4 ; 1514]	[-23.77 ; 495]	[14.27 ; 156.5]	[11.65 ; 106]	[9.715 ; 93.62]
	Sanderson-Windmeijer Weak id. F Stat.	3.579	5.837	21.04	28.16	25.68
	Sanderson-Windmeijer Weak id. p-value	0.0587	0.0158	<0.001	<0.001	<0.001
	Kleibergen-Paap weak IV Stat.	3.579	5.837	21.04	28.16	25.68
	Kleibergen-Paap Under id Stat.	3.607	5.854	21.85	28.99	26.31
	Kleibergen-Paap Under id p-value	0.0575	0.0155	<0.001	<0.001	<0.001

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department. CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent. *** p<0.01, ** p<0.05, * p<0.1

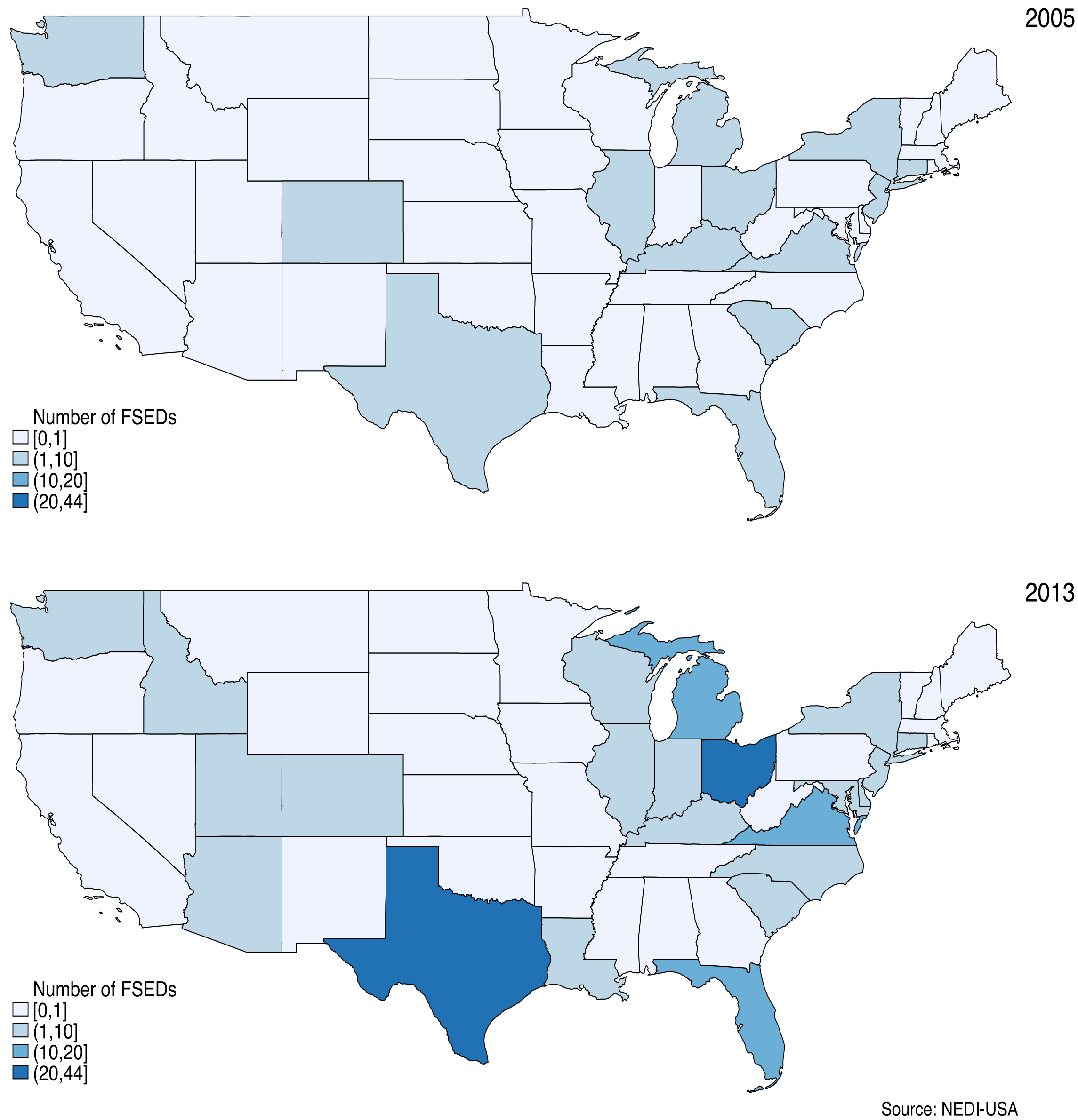
Table 30. Payer Mix ad hoc analysis, Number of Freestanding Emergency Departments operated – Instrumental Variables results.

All Areas	Number of FSEDs operated	-0.261*
		(0.133)
		-91.27
		[-182.7 ; 0.13]
	Sanderson-Windmeijer Weak id. F Stat.	8.537
	Sanderson-Windmeijer Weak id. p-value	0.004
	Kleibergen-Paap weak IV Stat.	8.537
	Kleibergen-Paap Under id Stat.	9.034
	Kleibergen-Paap Under id p-value	<0.001
Metropolitan Areas	Number of FSEDs	-0.104
		(0.0907)
		-36.36
		[-98.30 ; 25.57]
	Sanderson-Windmeijer Weak id. F Stat.	8.274
	Sanderson-Windmeijer Weak id. p-value	0.004
	Kleibergen-Paap weak IV Stat.	8.274
	Kleibergen-Paap Under id Stat.	9.026
	Kleibergen-Paap Under id p-value	<0.001

Standard errors in parentheses, clustered at the hospital level. In italics is the percent change in the outcome represented by the coefficient. In brackets is the 95% Confidence Interval of this percent change. FSED: Freestanding Emergency Department.

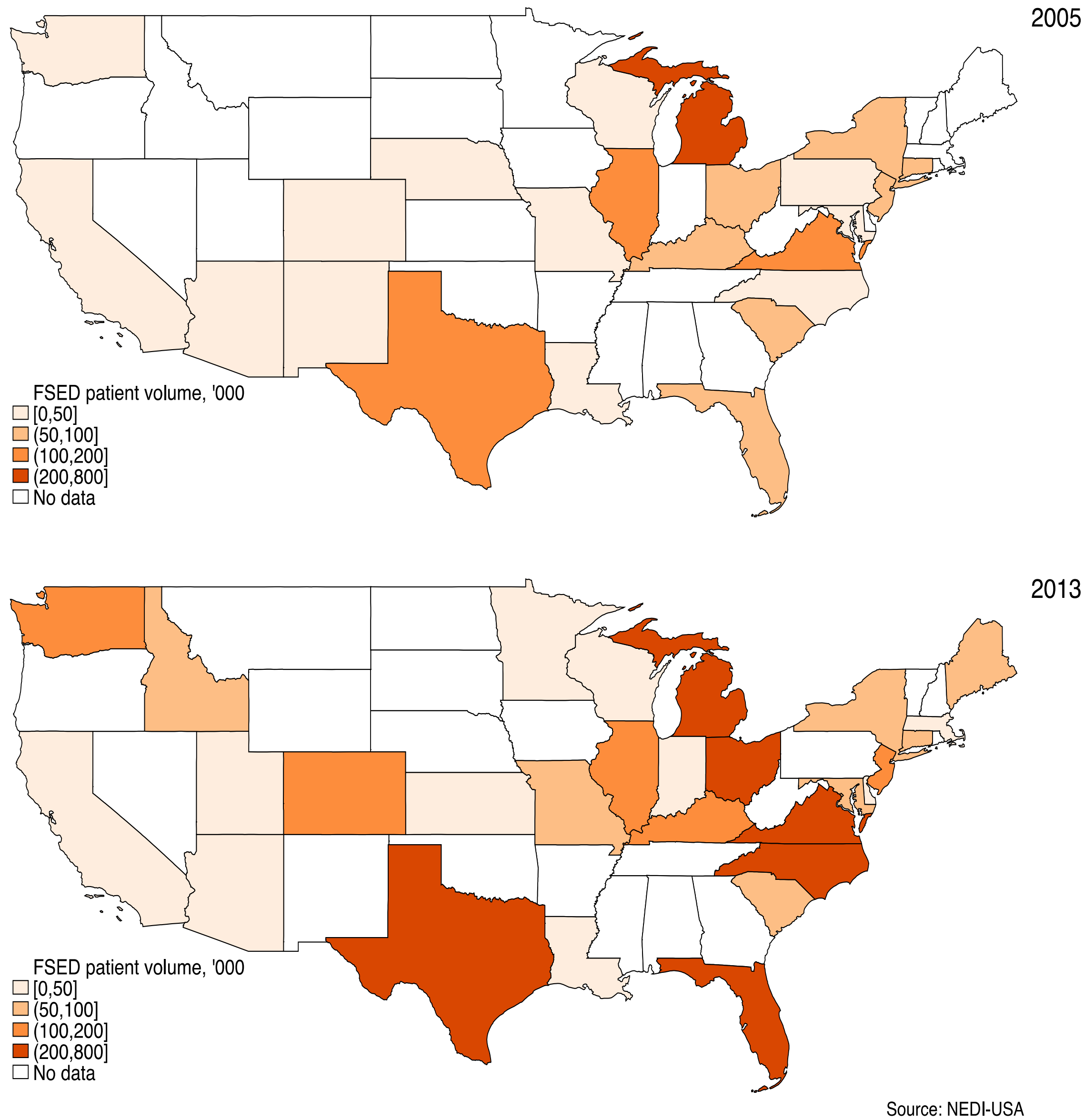
CASETA: Cases adjusted by transfers. CMI: Case mix index. TACMI: Transfer-adjusted Case mix index. DSHPT: Disproportionate Share Percent. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1. Number of FSEDs by state, 2005 and 2013



FSED: Freestanding Emergency Department.

Figure 2. Number of visits in FSEDs, 2005 and 2013



FSED: Freestanding Emergency Department.

Figure 3. Distance to closest ED, 2013.

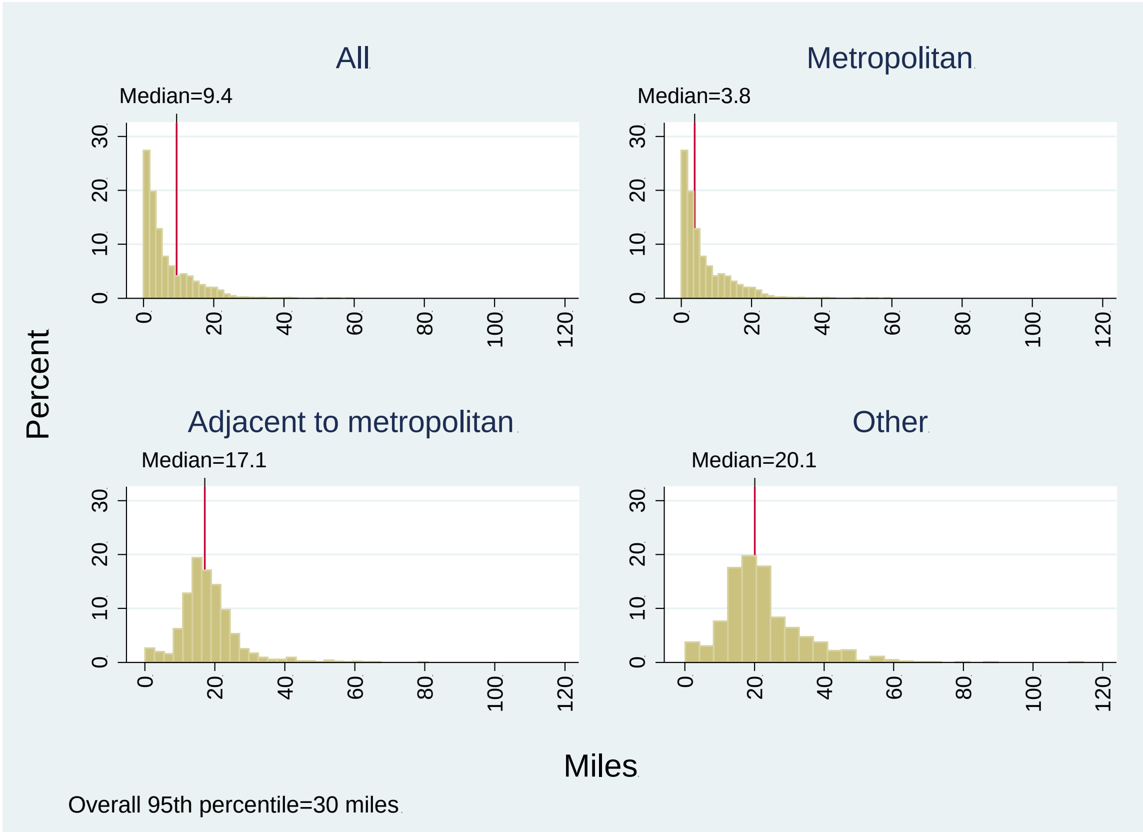


Figure 4. Average number of neighbors per ED within specified geographic location distance.

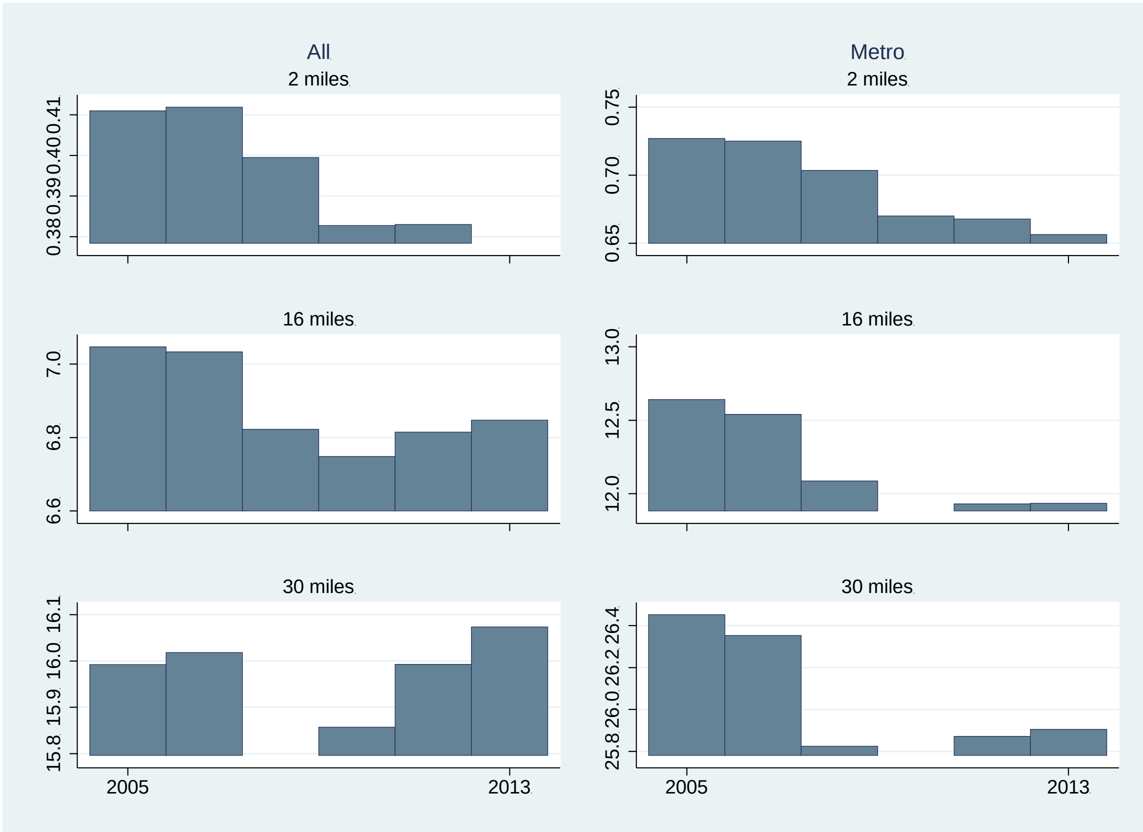


Figure 5. Percentage of EDs with entrants and exits within specified geographic location distance.

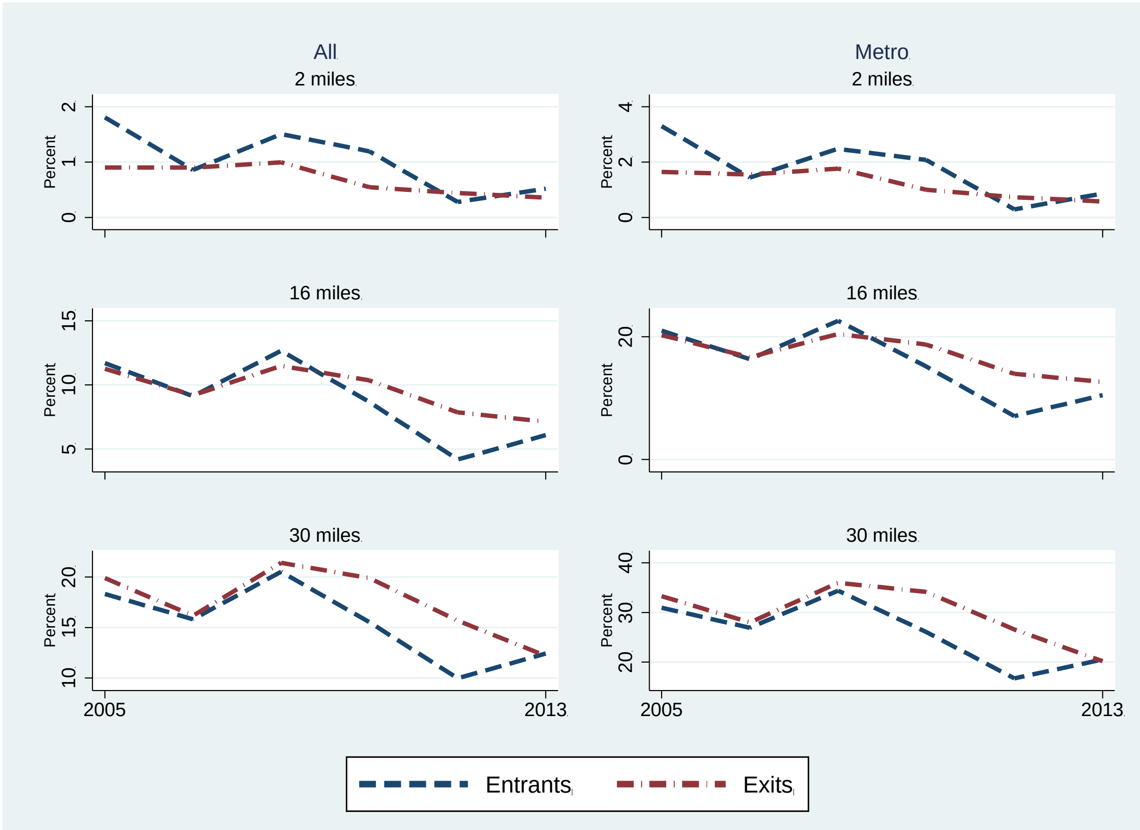


Figure 6. Conditional mean of number of entrants and exits.

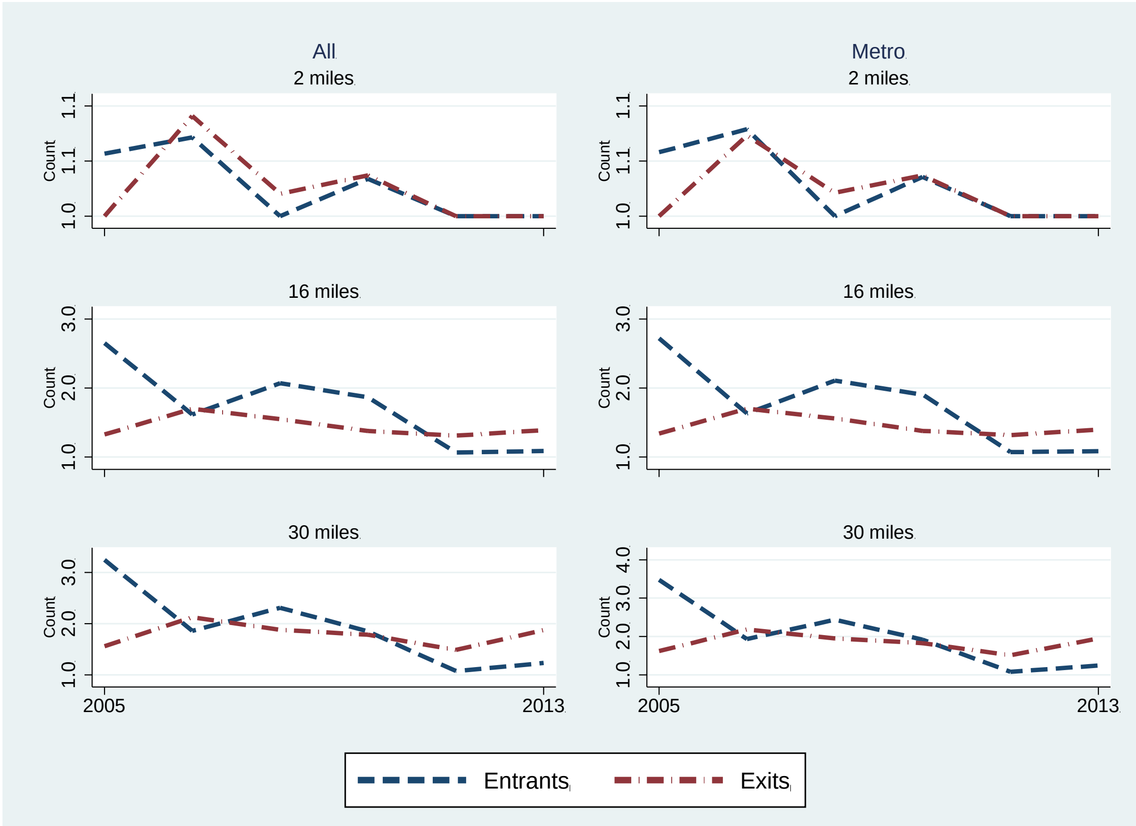


Figure 7. Predicted number of visits from basic OLS models.

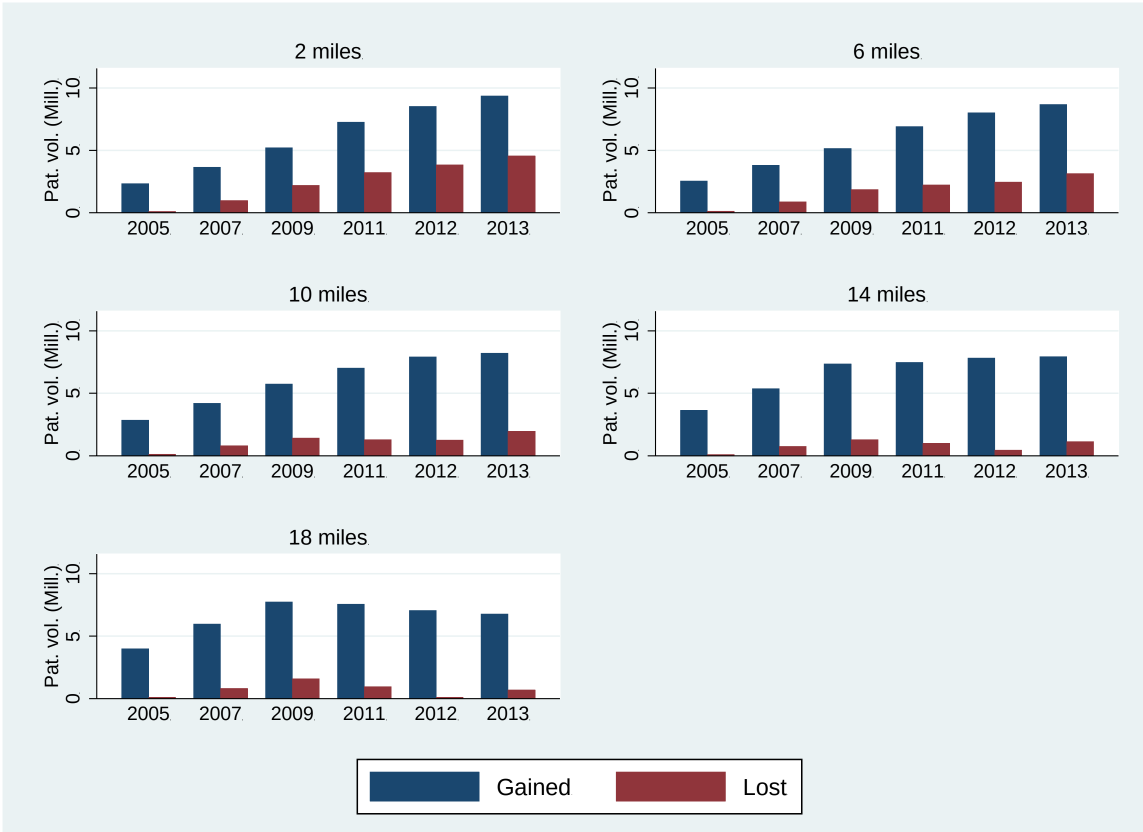


Figure 8. Predicted number of visits from OLS models with interactions.

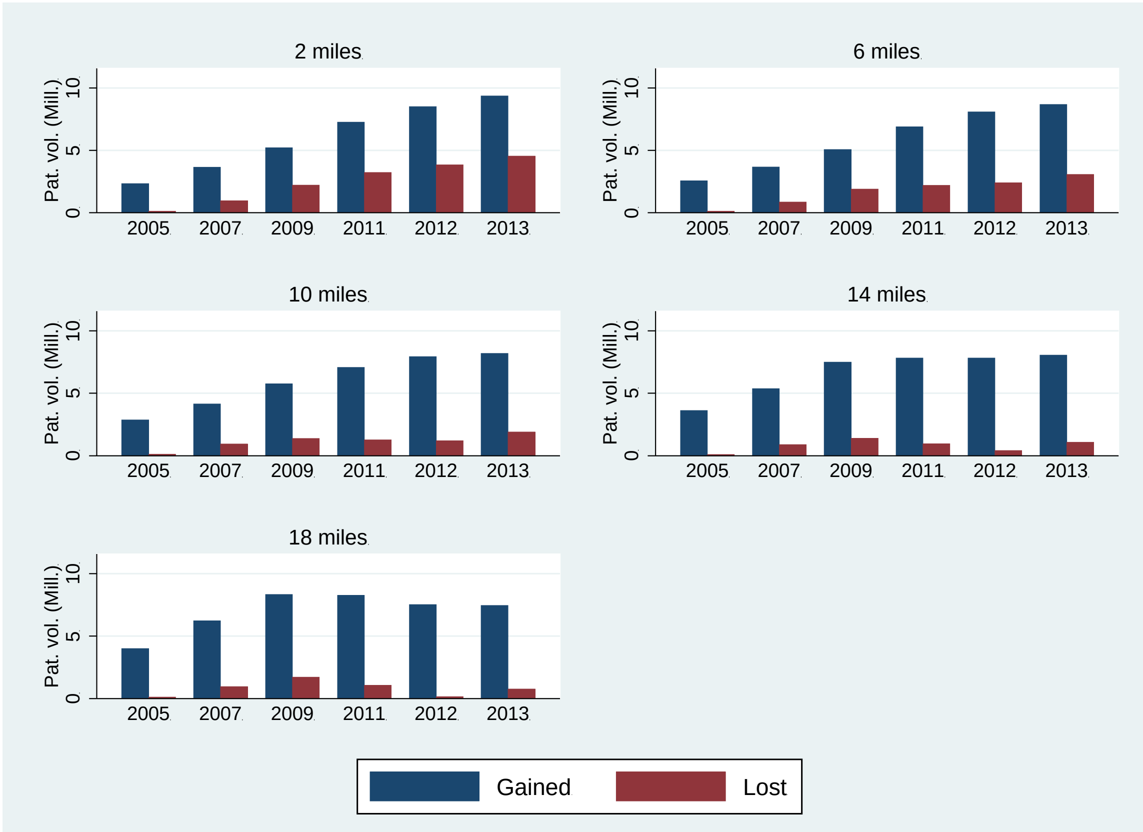


Figure 9. Predicted number of visits from IV models.

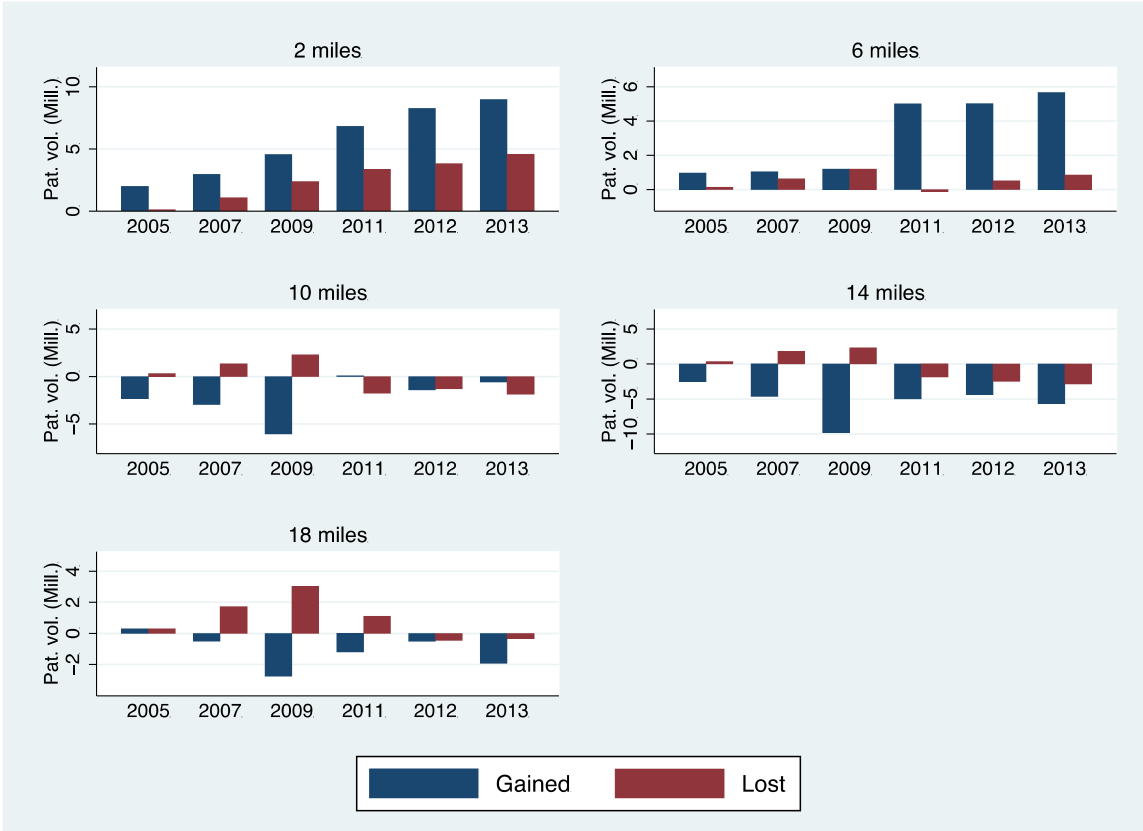
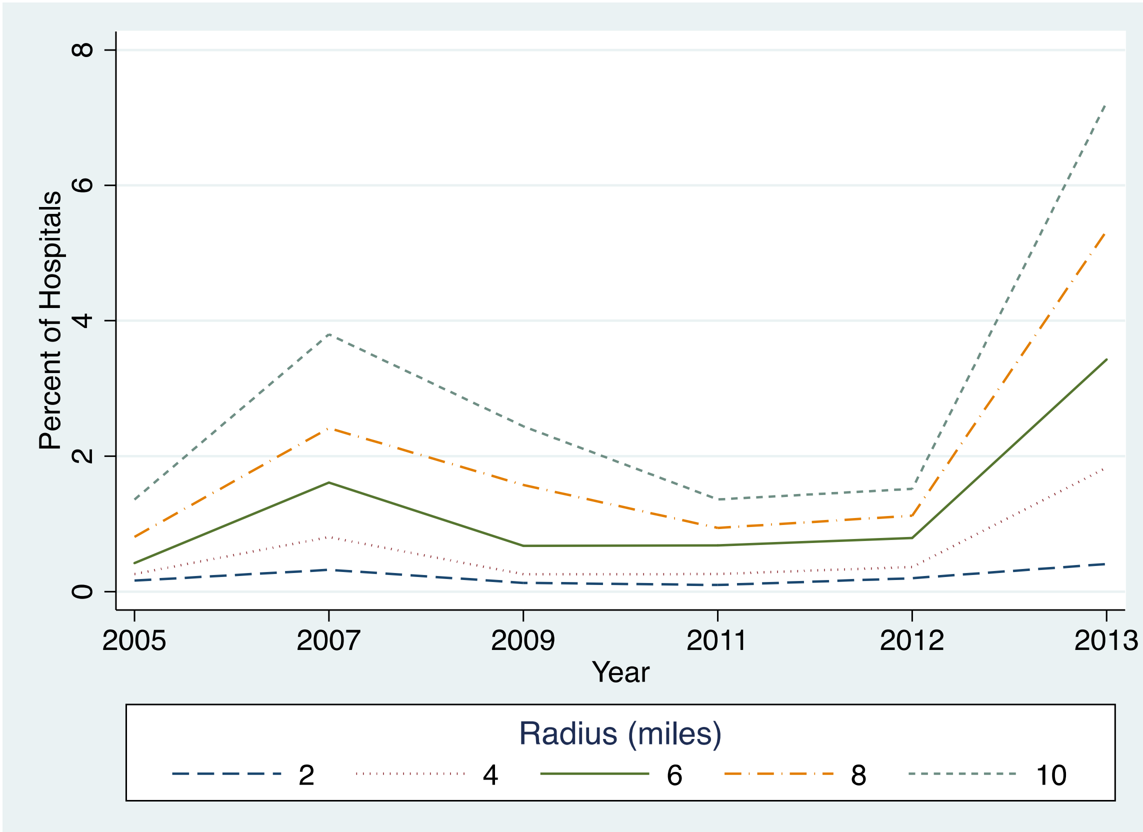


Figure 10 Percent of hospitals with an FSED within radius



FSED: Freestanding Emergency Department.

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